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NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

DISSERTATION

**EXTENDING ORGANIZATIONAL CONTINGENCY
THEORY TO TEAM PERFORMANCE – AN
INFORMATION PROCESSING AND KNOWLEDGE
FLOWS PERSPECTIVE**

by

Tara A. Leweling

September 2007

Dissertation Co-Supervisors:

Mark Nissen
John Arquilla

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13. ABSTRACT (maximum 200 words) Contemporary organizational theory posits that teams undertaking complex tasks outperform when lateral, peer-to-peer relationships are emphasized over vertical, subordinate-to-supervisor relationships. Outlining my argument within a structural contingency framework, I suggest that the intersection of the information processing structures and the contingent influence of knowledge sharing is an underexplored avenue for explaining variance in individual and team performance. I use a laboratory setting to explore this theoretical intersection. I manipulate the knowledge sharing processes and information processing structures of four multi-person teams as they undertake a series of computer-mediated counterterrorism decisionmaking exercises with high task complexity and reciprocal interdependency. I analyze the experimental results to explore the relationships between individual team performance and 1) differentiated information processing structures, 2) ability to share knowledge, and 3) interactions between these two manipulations. Each team repeats a variant of the same counterterrorism decisionmaking exercise four times and two of the four teams switch configurations halfway through the experimental series, allowing me to explore individual and team performance 1) cross-sectionally, 2) over time (i.e. learning) and 3) across structural reconfigurations. By way of contribution, this work extends structural contingency theory to work groups through the lenses of information processing and knowledge sharing in order to examine their putative effects on individual and team performance cross-sectionally, longitudinally, and when subjected to structural change.				
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**EXTENDING ORGANIZATIONAL CONTINGENCY THEORY TO TEAM
PERFORMANCE – AN INFORMATION PROCESSING AND KNOWLEDGE
FLOWS PERSPECTIVE**

Tara A. Leweling
Major, United States Air Force
B.A., University of Michigan, 1992
M.S., Troy State University, 2000
M.S., Naval Postgraduate School, 2001

Submitted in partial fulfillment of the
requirements for the degree of

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from the

**NAVAL POSTGRADUATE SCHOOL
September 2007**

Author:

Tara A. Leweling

Approved by:

Mark Nissen
Professor of Information Sciences
Dissertation Committee Chair &
Co-Supervisor

John Arquilla
Professor of Defense Analysis
Dissertation Co-Supervisor

Alex Bordetsky
Associate Professor of Information
Sciences

Erik Jansen
Senior Lecturer of Information
Sciences

Frank Barrett
Professor of Business and
Public Policy

Karl Pfeiffer
Assistant Professor of Information
Sciences

Approved by:

Dan Boger, Chair, Department of Information Sciences

Approved by:

Julie Filizetti, Associate Provost for Academic Affairs

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ABSTRACT

Research on contemporary work teams is vibrant and diverse, particularly as organizational theorists study the relationship of organizational performance and various work team attributes (e.g., self-management, empowerment, heterogeneity, shared situational awareness, others). Emerging from this literature is an emphasis on lateral, peer-to-peer work relationships over vertical, subordinate-to-supervisor work relationships as a rational organizational response to increasing task complexity in post-industrial economies. Although at the work group, rather than organizational or field level, such approaches clearly evoke contingent-theoretic arguments involving the influence of work structure and various contingency factors on performance. In essence, teams undertaking complex tasks are posited to outperform when lateral, peer-to-peer relationships are emphasized over vertical, subordinate-to-supervisor relationships, particularly when teams face particular contingent circumstances, such as task complexity and interdependence.

Contemporary expressions of organizational contingency theory hypothesize that the interaction of structural dimensions of work design (e.g., differentiation, formalization and centralization) and contingency factors (e.g., knowledge sharing) influence organizational adaptation to, and hence performance within, its environment. Although the relationship between artifacts of modern work and team performance has been investigated via a variety of constructs (e.g., efficacy, personality, culture, information processing, others), recent studies suggest that the contingent effects of knowledge sharing on team performance may be underexplored. Specifically, current scholars propose that exploring the interaction of knowledge flows and information processing structures could prove informative for explaining variance in collective performance. Further, while structural contingency theorizing is generally posited at the organizational level of analysis, researchers have recently explicitly articulated its utility for explaining performance within work teams. Thus the convergence of the information processing, structural contingency and knowledge flows research traditions – particularly as applied to work teams – represents an exciting opportunity to inform many dimensions

of the Information Sciences hydra. To the extent that “flattened” work team structures offer a parallel to network organizing, this theoretical confluence may also prove informative to those studying the performance of information processing networks within complex task settings.

From the intersection of these traditions, I construct a theoretical model and subject it to experimental examination. I guide the empirical inquiry with nine hypotheses related to the influence of information processing structure and knowledge sharing as a contingency variable on individual performance, individual learning, team performance and team learning. I divide 69 mid-level working professionals into four teams, then use a laboratory setting to manipulate the teams’ knowledge sharing and information processing structures during a series of computer-mediated counterterrorism decisionmaking exercises. I analyze the experimental results to explore the relationships between individual and team performance and 1) differentiated information processing structures, 2) ability to share knowledge, and 3) interactions between these two manipulations. Each team repeats a variant of the same decisionmaking exercise four times and two of the four teams switch configurations midway through the experimental series, allowing me to explore individual and team performance 1) cross-sectionally, 2) over time (i.e., learning) and 3) across structural reconfigurations (i.e., change). The experimentation suggests that the model offers explanatory value for individual performance, individual learning, and team performance. The experimentation also assists with deriving six postulates to motivate future work.

By way of contribution, this work extends contingency theory to work groups through the lenses of information processing and knowledge sharing to examine the putative effects of both, and their interactions, on individual and team performance cross-sectionally, longitudinally, and when subjected to structural change. It synthesizes three diverse but related literatures, reflecting and embedding core elements of the theories within a compact and integrative theoretical model. It tests this model via experimentation and suggests important postulates to motivate subsequent work.

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I. MOTIVATION

In this chapter, I describe the motivation for my work and discuss its theoretical framework of structural contingency theory, highlighting differences between classic and contemporary perspectives as well as how others have related and extended the theory to various theoretical constructs. I argue that examining the intersection of structural contingency, information processing and knowledge flows theories offers a constructive lens for explaining team performance. In so doing, I extend concepts that have reached high levels of consensus within the organizational literature – such as centralization and formalization – to teams, and I sketch the meaning of those concepts from an information processing viewpoint. I also note that through fieldwork and computational experimentation, our understanding of information flows within organizations is becoming increasingly sophisticated. In contrast, I observe that the influence of contingent knowledge flows on collective performance is underexplored. This theoretical gap between well-theorized information processing structures and the emergent construct of knowledge sharing suggests an interesting but underdeveloped theoretical space within information science – a space that could prove particularly important for explaining collective performance.

Throughout this work, I suggest that the interactive effects of information processing structures and knowledge sharing on collective performance require greater investigation, particularly when groups or teams undertake complex tasks. To motivate my work, I begin by observing that many practitioners and researchers describe the current organizational landscape as one of increasing dynamicism and complexity, with growing emphasis on lateral work relationships and team outcomes. I then briefly discuss structural contingency theory and identify how variants of the theory are used to explain collective performance. I argue that understanding the relationship(s) among key theoretical components (i.e., structure, contingency and performance) is critical for integrating scholarly contributions built within these frameworks. I then suggest that viewing work structure via an information-processing lens has proven a particularly powerful means for explaining collective performance, and thus argue for its continued

use in exploring team performance in this work. Moreover, recent scholarly work suggests that in addition to information processing structures, knowledge flows serve as an important contingency influencing collective performance, suggesting a unique – but underexplored – theoretical intersection for exploring collective action. I then ground this theoretical intersection firmly within the information sciences field, and I argue that the explicit controls of laboratory experimentation are well-suited for carefully examining the interaction of information processing structure, knowledge flows, and collective performance while controlling for exogenous variables. I close by briefly describing a program of experimentation for testing hypotheses generated at this unique and promising theoretical intersection.

A. PROBLEM STATEMENT

In this section, I briefly highlight a growing trend in the literature to describe contemporary work as increasing in complexity and interdependence. I relate this trend to concurrent assertions in the literature that organizations of many types are emphasizing team outcomes as important predictors of organizational success.

1. Landscape of Contemporary Work

Research on contemporary work teams is vibrant and diverse (for reviews, see Levine & Moreland 1990; Guzzo & Dickson 1996; Ilgen et al. 2005; Stewart 2006), particularly as organizational theorists credit creation of cross-functional teams as a rational organizational response to increasing task complexity in post-industrial economies (Kozlowski et al. 1999; Katz-Navon & Erez 2005; Kozlowski & Ilgen 2006). Harris and Harris (1996), for example, assert increased environmental complexity and uncertainty as a “fundamental reality” of contemporary work, suggesting that interdependent and collaborative teaming results in successfully performing within complex contexts. Similarly, DiMaggio (2001) and others (Kanter 1983; Hammer & Champy 1993; Baron et al. 1999) argue that contemporary management philosophy has favored lateral work relationships, collaboration and teamwork for over two decades,

resulting in “today’s entrepreneurs often building such philosophies into the organizations they design.” (DiMaggio 2001 p. 217)

Yet little is known about the putative benefits of this trend, which DiMaggio (2001) characterizes as the “widespread ... flattening of management structures” (p. 215) within contemporary organizations, relative to alternatives. The effects of “flat” work structures, however, persist as an important topic of discourse within organizational studies, suggesting that the topic retains intrigue for researchers, particularly those interested in organizational design (e.g., Hall 1963; Chisholm 1989; Daft 2001; Harris & Raviv 2002). This persistence implies that while much has been posited about the influence of flattened work structures on collective performance, lingering questions remain. Further, as new theoretical concepts are articulated and defined (for example, knowledge flows), it becomes prudent to re-examine existing knowledge in light of those theoretical developments, as well as to carefully explore and answer important questions introduced by these new concepts.

2. Structural Contingency Framework

Structural contingency theory (Burns & Stalker 1961; Lawrence & Lorsch 1967b; Hage & Aiken 1969; Pugh et al. 1969; Galbraith 1973; Drazin & Van de Ven 1985; Donaldson 1987; Donaldson 2001) begins to offer a cogent explanation for the trend toward organizational conditions that emphasize lateral (vice vertical) work relationships. Contingency theory emphasizes the fit of differentiated organizational structures to variegated environmental conditions (Katz & Kahn 1966; Thompson 1967; Donaldson 2001; Burton & Obel 2004). The theory suggests organizations adapt into structures suited to their experiential contingencies, which may vary on dimensions such as operating environment (e.g., complexity and dynamicism, see Duncan 1972), task and technology (e.g., task interdependence, see Thompson 1967; task routineness, see Perrow 1967), and competitive landscape (e.g., homogeneous versus heterogeneous customer base, see Pennings 1987). Contingency theory further suggests that for particular types of tasks, environmental conditions, or combinations of both, certain work structures clearly outperform available substitutes, and that changes within these structures over

time represent organizational adaptation (Westwood & Clegg 2003). The emergence of work structures that emphasize peer-to-peer relationships within organizational teams assigned complex tasks, then, can be modeled within a contingent-theoretic framework of 1) structure (e.g., “flat,” see Porter & Lawler 1964; Dalton et al. 1980; DiMaggio 2001), 2) contingency (e.g., task complexity, see Campbell 1988, Frost & Mahoney 1976; knowledge sharing, see Becerra-Fernandez & Sabherwal 2001, Birkinshaw et al. 2002; task routineness, see Perrow 1967), and 3) performance (e.g., effectiveness of output relative to goal). Figure 1 provides an abstract representation of the structural contingency framework for exploring collective performance.

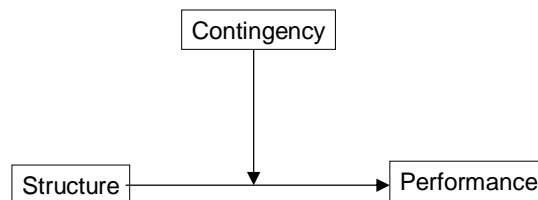


Figure 1. Contemporary Contingency Theoretic Framework

In short, organizations with structures that “fit” their respective environments (i.e., their respective contingencies) more coherently are posited to outperform those that do not, a postulate that receives support in the extant literature (Drazin & Van de Ven 1985; Naman & Slevin 1993; Jennings & Seaman 1994; Payne 2006). While the concept of fit often faces challenges due to inadequate construct specificity (Schoonhoven 1981), unwarranted generalizations (Tosi & Slocum 1984), insufficient multi-level theorizing (Tosi & Slocum 1984), overemphasis on deterministic aspects (Weill & Olson 1989), and overlap of theoretical terminology (Venkatraman & Camillus 1984), this incoherence provides an opportunity to contribute to the literature by clarifying key constructs within the theoretical traditions forming the core of this work. These challenges also suggest that careful research designs grounded in a clearly articulated theoretical model and controlling for exogenous influences may be particularly helpful for illuminating relationships among structure, contingency and performance.

a. Early Structural Contingency Theory

Within structural contingency theory, the theoretical relationships among structure, contingency and performance have evolved over four decades of theorizing. Rather than contingency moderating the relationship between structure and collective performance, as Figure 1 might suggest, early structural contingency work viewed the role of contingency as a predictor (i.e., mediator), not moderator, of structure. This distinction in the relationship between structure and contingency is subtle, but important. Early contingency work, which Miner (2002; see also Dalton et al. 1980) contends receives inconsistent levels of empirical support, suggests an arrangement in which contingent conditions are solely, or at least primarily, predictive of organizational structure. In turn, organizational structure is posited to predict organizational performance. This early contingency theorizing is illustrated in Figure 2¹ and reflects the difference of the viewing the contingency-structure relationship as one of moderating (i.e., Figure 1) versus mediating (i.e., Figure 2) variables.

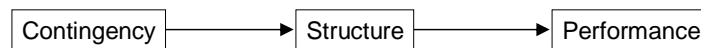


Figure 2. Early Contingency Framework

b. Contemporary Contingency Theory

The distinction between Figure 1 and Figure 2 may appear semantic, but Gresov and Drazin (1997) assert that contemporary expressions of contingency theory involve multivariate constructs and even multi-level theorizing. In their view, the early contingency framework depicted in Figure 2 has limited explanatory value. Gresov and Drazin (1997) instead counter that multivariate *interactions* of contingency and structure more ably explain variance in performance. Gresov and Drazin's (1997) view contrasts with over the more linear perspective of specific structural variables serving as predictors of performance and particular contingency variables serving as the predictors of structure

¹ Aldrich and Pfeffer (1976) refer to this approach as the 'natural selection model' while Westwood and Clegg (2003) refer to it as 'structural determinism.'

evident in the early contingency framework depicted by Figure 2. As Lenz (1981) argues, distinctions between the two approaches help to differentiate related empirical studies based on the types of assumptions undergirding their theoretical constructs – i.e., 1) studies that posit a causal relationship between contingency and structure (see e.g., Child 1975; Drazin & Van de Ven 1985), 2) studies that posit a causal relationship between structure and performance (see e.g., Carzo Jr. 1963; Reimann 1974; Pennings 1975), or 3) studies that posit interactions of structure *and* contingency influence performance (see e.g., Lawrence & Lorsch 1967a; Jennings & Seaman 1994; Keller 1994; Becerra-Fernandez & Sabherwal 2001).

c. Strategic Choice and Structural Contingency Theory

Extensions to contemporary contingency theory include emphasis on how factors other than traditional dimensions of contingency and structure combine with other dimensions of organizational life (e.g., strategic choice, see Child 1972; Hambrick 1983; Govindarajan 1986; culture, see Deshpande & Webster 1989) to affect observed performance. These extensions represent important attempts to link strategic management and contingency-related theorizing, and the models are often labeled as the configurational approach toward organizational design and analysis (for a review, examples and further discussion; see Doty et al. 1993; Meyer et al. 1993; Morrison & Roth 1993; Snow et al. 2005; Payne 2006). An example of the type of relationships posited in this literature is illustrated at Figure 3 with strategy moderating the relationship between contingency and structure. Epistemically, these extensions begin to integrate humanist assumptions into the structural contingency framework, carving a theoretical space for concepts such as management interventions (Covin & Slevin 1989; Doty et al. 1993) to counterbalance more deterministic interpretations of structural contingency theory.

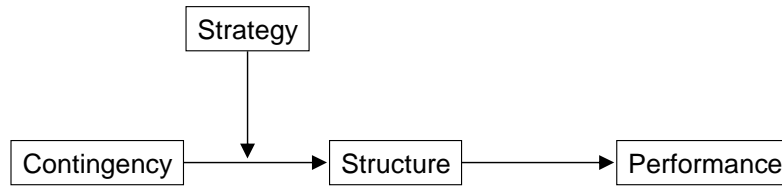


Figure 3. Linking Strategic Choice and Contingency Theory

d. Relationship to Information Processing, Knowledge Flows, and Laboratory Experimentation

As will be discussed in later sections, structure can be viewed and operationalized via an information processing lens, and an important contingency emerging in recent work (Rulke & Galaskiewicz 2000; Birkinshaw et al 2002; Hutzschenreuter & Listner 2007) is knowledge transfer. By arguing that the information processing structures within teams predict performance – but that the relationship between information processing structures is moderated by the contingency variable of knowledge sharing (Birkinshaw et al. 2002) – this dissertation is most consistent with the contemporary contingency theory approach illustrated in Figure 1. The present research builds upon Birkinshaw et al’s (2002) finding that knowledge sharing serves as an important contingency variable for work design, but adjusts the theoretical construct from one of expecting knowledge sharing to *predict* structure to one of expecting knowledge sharing to *moderate* the relationship between structure and performance (e.g., Rulke & Galaskiewicz 2000). The theoretical construct is thus consistent with findings suggested by prior empirical work (e.g., Rulke & Galaskiewicz 2000; Becerra-Fernandez & Sabherwal 2001; Birkinshaw et al. 2002), but closes a gap in the literature through the explicit testing of *interaction* effects between information processing structures and knowledge sharing as a contingency variable.

By narrowing the scope of inquiry to how information processing structures and contingent knowledge interact to influence performance, the theoretical construct avoids becoming confounded (Shadish et al. 2002) with the dozens of variables that could reasonably be included in a contingency approach for explaining the performance of work teams. Moreover, calls for narrower, more clearly explicated studies when using

contingency frameworks (Schoonhoven 1981; Orlikowski 1992) suggest that laboratory experimentation can assist researchers to explore both persistent and emergent questions raised by field studies undertaken within the contingent-theoretical framework. Indeed, exploring theoretical relationships inside laboratory settings with human subjects contributes to “full cycle” organizational research (Chatman & Flynn 2005) and serves as a natural complement to related work undertaken in field (Woodward 1965; Reimann 1973; Cheng & McKinley 1983; Drazin & Van de Ven 1985; Keller 1994) and computational (Carley & Hill 2001; Levitt 2004; Nissen & Levitt 2004; Nissen & Sengupta 2006) settings. Specificity associated with laboratory settings also responds to Schoonhoven’s (1981) comment that studies grounded in contingency theory produce inconsistent results, with insufficient clarity and precision in the research designs ascribed as one of the primary causes of the inconsistencies. Intuitively, then, using a laboratory setting to explore the interaction of information processing structures and contingent knowledge flows on collective performance appears to address concerns about specificity of constructs and consistency (particularly repeatability) of empirical results voiced throughout the contingency literature.

B. TEAMS AND STRUCTURAL CONTINGENCY THEORY

Levels of analysis for research informed by structural contingency theory have primarily centered upon organizations and organization populations (e.g., Schoonhoven 1981; Pennings 1987), although interesting contingent-theoretic work has also emerged within inter-organizational (e.g., Burt et al. 1994) and work group (e.g., Keller 1994) settings. Perhaps surprisingly, units of analysis for organizational contingency studies have often been managers, top management teams or small work groups (see e.g., Baumler 1971; Reeves & Turner 1972; Argote 1982). Hollenbeck et al (2002) argue that “there is value in expanding the idea of fit from the organizational level to the team level” (p. 599), and further suggest that theorizing about structure-contingency interactions at the team level could have significant explanatory power for team performance. This assertion is intuitively appealing, as reasonably-sized teams (e.g., Bavelas 1950 and Guetzkow & Simon 1955 used five-person teams in their pioneering studies) face many

of the same structural and contingency pressures as their organizational counterparts. Further, distinctions about the structure of work processes when comparing large teams and small firms are often difficult to explicitly identify, and concepts such as centralization, formalization, and differentiation apply equally well at multiple levels of analysis. The operationalization of concepts such as centralization, for example, will often appear very similar whether working with work groups, teams, divisions or organizations as the primary unit of analysis. Moreover, Ilgen et al.'s (2005) review of empirical and theoretical advances on work teams suggests that contingent-theoretic constructs could prove particularly useful for explaining team performance when team member interactions are viewed as knowledge sharing activities (e.g., Barry & Stewart 1997; Hyatt & Ruddy 1997; Mathieu et al. 2000; Marks et al. 2002; Engle 2004). Understanding the interaction on information processing structures with knowledge sharing using a contingency perspective, then, seems to offer significant promise for explaining variance in team performance, an enduring topic in the team literature (see e.g., Levine & Moreland 1990; Guzzo & Dickson 1996; Ilgen et al. 2005; Stewart 2006).

This is not to argue that the literature on team performance is without contingency-based theorizing; certainly contingency constructs have formed the basis of research designs and meta-analytical studies focused on teams over many decades (e.g., Priem 1990; Ancona & Caldwell 1992; Wiersema & Bantel 1992; Beersma et al. 2003). Similarly, such studies are often collated into a family of contingency theories relevant to a particular concept, such as leadership (see e.g., Yukl 2001). However, as Hollenbeck et al (2002) assert, structural contingency theory (i.e., fitting team to task) is a promising, and underexplored, extension of traditional team literature notion of fitting individuals to their teams. For Hollenbeck et al (2002), the power of structural contingency theory for understanding team performance is the refocusing theoretical emphasis from fitting persons to teams (e.g., Kristof 1996) to fitting teams to tasks.

C. AN INFORMATION PROCESSING VIEW OF STRUCTURE

The meaning of “structure” varies across the contingent-theoretic tradition, but common to most work in the domain is defining work activities along core dimensions of

centralization / decentralization, formalization / standardization, and differentiation / specialization (Pugh et al. 1968; Hage et al. 1971; Dalton et al. 1980; Fry & Slocum 1984; Miller et al. 1991; Doty et al. 1993; Levitt et al. 1999; Daft 2001). Scholars often delineate along these dimensions to distinguish one ideal type of work structure from another (e.g., Mintzberg 1980; Doty et al. 1993). At the team level, Katz-Navon and Erez (2005) argue that task interdependence is another important component of structure, as task interdependence “shapes the links among the different roles in the team and the coordination requirements from the team members” (p. 400, see also Kozlowski et al. 1999). This argument parallels Thompson’s (1967) identification of the level of interdependence among organizational agents (i.e., pooled, sequential or reciprocal) as an important consideration in organizational design. Combining these perspectives, then, a view of team structures emerges that focuses upon intrateam work relationships. Specifically, centralization, formalization, differentiation and interdependence emerge as core concepts of team structure.

Building upon the basic contingency framework, Galbraith (1973) extends these core dimensions of structure – i.e., centralization, formalization, specialization and interdependence – from the traditional lens of organizational power dynamics (e.g., Hage & Aiken 1967; Miller & Friesen 1978; Courpasson 2000) to the domain of organizational information processing. For an organization to reduce its information processing needs, Galbraith (1973; see also Premkumar et al. 2005) suggests two design strategies: 1) creating slack within an organization’s information seeking and sharing processes (i.e., reducing information interdependence and increasing information redundancy among organizational agents) and 2) creating self-contained tasks (i.e., increasing specialization of information processing among organizational agents). To improve information processing capacity, Galbraith (1973; see also Premkumar et al. 2005) suggests an additional two strategies for organizational design: 1) investing in vertical information systems (i.e., formalization of information processing, such as routinization of accounting procedures) and 2) creating lateral relations for information seeking and sharing (i.e., decentralization of information processing, such as allowing access to information to be diffused across multiple intraorganizational agents). Table 1 summarizes Galbraith’s

perspective of organizational information processing as related to dimensions of structure common to the contingency theory literature. Through his extension of these concepts, an information processing view of structure begins to emerge.

Goal	Galbraith's Strategy for Responding to Environmental Complexity and Dynamicism	Example – Organizational agent A's work designed such that:	Related Dimension of Structure
Reduce need to process information	Create slack	A's tasks are minimally impacted if B provides late or incorrect information	Interdependence
	Create self-contained tasks	A's tasks can be completed using information organic to A	Specialization
Enhance capacity for processing information	Create vertical information systems	A provides B with similar information in a similar format	Formalization
	Create lateral relations	A seeks information from functional peer B more than supervisor C	Centralization

Table 1. Dimensions of Structure within Galbraith's (1973) Information Processing Model

As the uncertainty of an organization's environment increases, Galbraith (1973) argues that an organization designed for 1) low interdependence, 2) high specialization, 3) high formalization and 4) low centralization among its information processes would outperform counterparts with structures operating at different points in this four-dimensional design space. By reducing its need to process information (i.e., through low interdependence and high specialization) while simultaneously improving its capacity to process information (i.e., through high formalization and low centralization), the organization reduces environmental uncertainty. In effect, through improving the structure of its information processing functions, organizational work units create a buffer in which a complex and dynamic environment appears more simple and stable.

As Levitt and others have demonstrated (Egelhoff 1982; Levitt et al. 1994; Jin & Levitt 1996; Levitt et al. 1999; Levitt 2004; Levitt et al. 2005; Thomsen et al. 2005), viewing work structures within an information processing framework allows

organizational designers to develop and test contingency theory in new and exciting ways. The information processing lens allows researchers to look beyond traditional contingency relations grounded in constructs of authority and strategic choice (Child 1972; Ginsberg & Venkatraman 1985; Govindarajan 1986), size and managerial span of control (Ford & Slocum 1977; Lee et al. 1982), or technology (Perrow 1967; Fry & Slocum 1984). The information processing lens allows researchers to instead focus upon the meaning of contingency theory for micro-organizational processes within projects, work groups and/or teams (Levitt et al. 1999; Thomsen et al. 2005). This approach may also reveal new insights into the interactions of micro-level organizational processes generating new insights not only about micro-level interactions, but also emergent macro-level behaviors and effects.

Organizational information processing is proving especially fruitful for exploring how variance in work flows among organizational agents affects overarching performance in varying contexts (Kunz et al. 1998; Nissen & Levitt 2004; Gateau et al. 2007; Leweling & Nissen 2007a). For example, work in this theoretical vein has demonstrated how reciprocal versus sequential interdependence (Thompson 1967) of organizational information flows affects performance, particularly when the task is complex (Jin & Levitt 1996). Similarly, work in this vein has examined how knowledge loss due to personnel turnover impacts collective performance (Devadas Rao & Argote 2006). Recent work has also explicitly introduced knowledge as an important influence on objective performance (Rulke & Galaskiewicz 2000; Birkinshaw et al. 2002; Nissen et al. 2004).

D. KNOWLEDGE AS A CONTINGENCY VARIABLE

Micro-organizational processes are receiving emphasis in other areas of organizational research framed in contingency theory, such as strategic choice (Johnson et al. 2003) and knowledge management (Nissen & Levitt 2004). Contemporary knowledge management theory (Nonaka 1994; Nissen 2006), for example, argues that within high performing organizations, work flows are tightly coupled with information and knowledge flows. To improve organizational performance (e.g., efficiency and

effectiveness), knowledge flows theorists suggest, organizations should structure information and knowledge flows to complement work flows and avoid information and knowledge processes that result in static “clumps” of knowledge that fail to contribute to organizational effectiveness (Nissen & Levitt 2004). These micro-organizational adjustments, contemporary knowledge management researchers contend, result in macro-level effects of improved work group, team, and/or organizational performance. Birkinshaw et al (2002) echo these arguments by explicitly asserting that knowledge is emerging as an important contingency variable, and more explicitly, that “characteristics of knowledge are an important predictor of organizational structure” (p. 234). Work by Rulke and Galaskiewicz (2000), as well as Becerra-Fernandez and Sabherwal (2001) and Hutzschenreuter and Listner (2007), supports incorporating knowledge into contingent-theoretic research designs focused on assessing its putative effects on organizational, team and work group performance.

E. FOCUS OF THIS RESEARCH

To complement and leverage existing field and computational studies related to our understanding of these relationships (e.g., Keller 1994; Rulke & Galaskiewicz 2000; Becerra-Fernandez & Sabherwal 2001; Birkinshaw et al. 2002; Kim & Burton 2002; Levitt 2004; Nissen & Sengupta 2006), I use laboratory experimentation to contribute to the “full cycle” theorizing process (Chatman & Flynn 2005). Grounding my investigation in the contemporary contingency framework, I study the interaction of knowledge sharing and information processing structures on team performance. I divide 69 mid-level working professionals into four teams, then use a laboratory setting to manipulate the teams’ knowledge sharing and information processing structures during a series of computer-mediated decisionmaking exercises. I analyze the experimental results to explore the relationships between individual and team performance and 1) differentiated information processing structures, 2) ability to share knowledge, and 3) interactions between these two manipulations. Each team repeats a variant of the same decisionmaking exercise four times and two of the four teams switch configurations at midway through the experimentation, allowing me to explore team performance 1) over

time (i.e., learning) and 2) across structural reconfigurations (i.e., change) as well as cross-sectionally. This research setting allows for consideration of substantive hypotheses (Kerlinger & Lee 2000) focused on organizational archetype (i.e., structure) and knowledge (i.e., contingency) within a highly complex and interdependent task environment.

F. RELEVANCE AND CONTRIBUTION OF RESEARCH

The view of human collectives as information processing systems (March & Simon 1958; Galbraith 1974; Feldman & March 1981) has long evoked contingent-theoretic arguments, particularly as the relationship between information, knowledge and uncertainty is explored in detail and leads to enhanced understanding of their intricacies.

1. Relevance and Contribution to Team Performance

Contingency theorizing is a long-established tradition within organizational studies, but only recently has structural contingency theory and the concept of fitness functions been explicitly considered as proffering explanatory power for team performance (Hollenbeck et al. 2002; Ilgen et al. 2005). Concurrently, the importance of linking knowledge flows to work flows to improve performance at various levels of organization has been advanced in recent years (Nissen & Levitt 2004; Looney & Nissen 2006; Nissen 2006; Nissen & Sengupta 2006). However, the *interactive* effects of information processing structures and knowledge sharing on team performance are relative unknowns. This lack of understanding is particularly acute when the assigned tasks involve complexity and high levels of interaction among team members – precisely the context that the organizational and team literatures suggest is emerging as the “fundamental reality” of knowledge economy work (Barley 1996; Dunphy & Bryant 1996; Harris & Harris 1996; Leifer & Mills 1996). The implications of exploring the relationships among information processing structures, knowledge flows and performance thus address a theoretical gap in the structural contingency, information processing, knowledge management and team performance literatures. Moreover,

findings from such research promise to be informative to practitioners who manage information, knowledge, and work flows in a wide variety of organizational contexts.

2. Relevance and Contribution to Information Science

Information science, as a field, diverges in both its theoretical lenses and key constructs (Saracevic 1992; Vessey et al. 2002; Raber 2003). Although information science is often associated with research on information systems (Borko 1968; Saracevic 1999), scholars lament that research on information technology seems increasingly distanced from other academic disciplines contributing to the field (Saracevic 1999), a circumstance that has been varyingly attributed to epistemological differences (Orlikowski & Barley 2001), irregularity among the meanings of core concepts (Markus & Robey 1988), or a tendency toward artifact-centered theorizing (Orlikowski 1992). Viewed abstractly, however, a consensus emerges about the field's primary phenomena of interest, broadly characterized as the study of human activities associated with information and information technology, such as "gathering, organizing, storing, retrieving, and disseminat[ing]" information (Bates 2003, p. 1044) as well as understanding bi-directional flows between data, information and knowledge (Nissen 2002). As Spink (2000) describes:

...Information Science research is concerned with how humans create, seek, retrieve and use information; particularly human interactions with information systems Information Science processes include human creating, seeking, retrieving and using information; particularly human interaction with information systems. Information Science focuses on many different processes that occur over time, including a human information problem that initiates information behavior related to a human problem state, cognitive state and knowledge state. (p. 73)

Saracevic (1992, as cited in Raber 2003) generally concurs, describing information science as:

...a field devoted to scientific inquiry and professional practice addressing the problems of effective communication of knowledge and knowledge

records among humans in the context of social, institutional and/or individual uses and needs for information. (p. 5)

Such descriptions are overly broad to meticulously distinguish the scientific discipline of studying information from related disciplines, but they do differentiate the field's phenomenological core from other concepts of social science inquiry—such as power, authority and social relations within organizations (see Lounsbury & Ventresca 2003 for a discussion). Chiefly, information science emphasizes inquiry into information exchange among human agents, as well as the technologies used to facilitate such exchanges. Like its counterparts within the social sciences, the meaning of “information” as an analytically tractable and bounded object of inquiry is contextually situated and subject to emerging scholarly consensus (and sometimes divergence). Clearly, however, studying the exchange of information among various agents via a variety of media falls squarely within the field's bounds as a core phenomenological interest. As Grant (1996b) points out in his knowledge-based theory of the firm, the “information view” of organizations requires focusing more on organizational coordination (which he attributes as an outcome of knowledge relationships among organizational actors) vice cooperation (which he attributes as an outcome of authority relationships among organizational actors). While achieving “purposeful, coordinated action from organizations comprising of many individuals” (p. 117) requires realizing *both* coordination and cooperation, Grant (1996b) contends that knowledge-based views of the firm require emphasis on the former.

3. Historical Precedent -- Information Technology and Contingency Theory

Artifact-based theorizing sometimes dominates information science (Huber 1990; Orlikowski 1992; Orlikowski & Iacono 2001), but the field appears to be moving toward theory-based rather than practice-based puzzle solving (Meadows 1990; Harter & Hooten 1992; Pettigrew & McKechnie 2001). Contingency theorizing, in particular, has played an important role within information science theorizing (Weill & Olson 1989). Sharma and Yetton (2007), for example, invoke a contingent-theoretic framework to explain the

effect of user training on implementation of information systems. Similarly, Hutzschenreuter and Listner (2007) develop a contingency theory model for knowledge transfer, and Thomsen et al (2005) explore the influence of information processing on goal congruency. Silva and Hirschheim (2007) invoke the contingency theory framework to explore the influence of exogenous contingent factors on decisions to implement strategic information systems. More generally, other contingency theorists postulate technology as a central variable to be considered when designing (and redesigning) organizations and work groups (Perrow 1967; Hickson et al. 1969; Blau et al. 1976; Fry & Slocum 1984; Markus & Robey 1988).

As Orlikowski and Robey (1991) note, viewing *information* technology as a contingency variable holds important explanatory power for understanding organizational work (see Pfeffer & Leblebici 1977; Carter 1984; Huber 1990). Orlikowski (1992), however, expresses dissatisfaction with divergent interpretations of how information technology should be incorporated into contingency theorizing. To forge a middle ground between classic and contemporary views of technology's role within organizational contingency theory, Orlikowski (1992) draws upon Giddens's structuration theory (1979; 1982) and Barley's (1986) demonstration that information technology interacts with *existing* organizational structures to *change* information flows and thus produce *new* organizational structures (for related work, see Mason et al. 1997; Silva & Hirschheim 2007). Specifically, Orlikowski (1992) suggests that both views of structural contingency (i.e., "structural determinism"² in which technology explains structure, and the configurational approach³ in which technology interacts with structure to produce organizational outcomes) are false dichotomies.

Orlikowski (1992) instead asserts that information technology—which she and Barley (2001) define as organizational information processes, not particular technological artifacts—must be viewed as an integral, analytically intractable part of organizational structures. Thus organizational information processing is neither an independent contingency variable that influences organizational structure, nor is it as an interactive

² Westwood & Clegg 2003

³ Dow 1988; Meyer et al. 1993

contingency variable that combines with organizational structure to influence performance. Rather, Orlikowski (1992) contends, information flows serve as one of the means through which organizational structuration occurs. Given this lens, bounding an organizational system requires including not only human agents, but also the information flows between these agents via various means of exchange. Put differently, information processes assist with creating and sustaining organizational structuration, and as a result, the processes provide a basis from which one can explore the implications of structure for collective performance. Given that some means of processing information involve transferring the information from one agent to another (i.e., creating a *flow* of information between two agents), we see that information flows and organizational structure, in Orlikowski's (1992) view, are entwined.

4. Contemporary Views -- Information Processes as Organizational Structure

Viewing an organization's information technology as the collective set of processes undertaken by the organization to manipulate its information provides a fresh perspective for information science theorizing. Using this framework, studies that seek to relate an organization's information technology (e.g., information flows) to the organization's task environment (e.g., stable-dynamic, simple-complex) become unconstrained by artifact-oriented conceptualizations. Such work can instead focus upon how changes to the information processing structures of the organizations influence subsequent outcomes. Work in this vein seems particularly suited for connecting macro-level, emergent outcomes more closely to micro-level organizational behaviors (see e.g., Ziguers & Buckland 1998) at multiple levels of organizational theorizing, an approach that Argote (1999) argues as important for creating cogent theory and explanation. Moreover, information processes—such as store, retrieve, send, receive, others—appear to transcend standard levels of analysis within organizational theorizing, just as certain dimensions of structure (e.g., centralization, formalization, differentiation) offer the same elasticity in their applicability to multiple levels of analysis. Viewing information structures, then, as the collection of activities involving the use of information by a team, work group, or

organizations, suggests that generalized results from their study could pertain to multiple levels of analysis within organizational life *simultaneously*.

We find ourselves at an exciting, interesting juncture for explaining variance in collective performance while building upon multiple theoretical traditions within a broadly-defined information sciences. The juncture builds upon March and Simon's (1958) views of organizations as decisionmaking organisms, as well as Galbraith's (1974; 1977) work to extend March and Simon's (1958) perspective into theoretical postulates about information processing. The intersection is further informed by the work of Levitt et al (1994; 1999) to operationalize, analyze, and refine Galbraith's (1974; 1977) propositions, as well as Orlikowski and Robey's (1991) extension of Giddens' (1979; 1982) structuration theories to organizational information processes. Nonaka's (1994) and Nissen's (2006) probing into the dynamic nature of knowledge flows contribute theoretical richness about differences between information and knowledge into this juncture. Further, Rulke and Galaskiewicz (2000) and Birkinshaw et al's (2002) identification of knowledge as an important contingency variable suggests how to consider this theoretical intersection through the long-standing contingency-theoretic lens. Finally, Hollenbeck et al's (2002) efforts to extend structural contingency theory (and the concept of fitting structure to task) to work groups assist with demarcating an important level of analysis for the inquiry. The convergence of these research traditions suggests that the intersection of information processing, structural contingency and knowledge flows theorizing at the work group level—and most importantly, their combined effect on observed performance—could be informative to many dimensions of the information sciences field.

G. ORGANIZATION OF WORK

In the chapters to follow, I discuss the proposed research in greater detail. Specifically, in Chapter II, I review the structural contingency, information processing and knowledge flows literatures. In the course of doing so, I construct a theoretical model undergirding my research. I also motivate nine hypotheses that allow this intersection to be explored in greater detail. In Chapter III, I articulate a program of

experimentation designed to empirically test the hypotheses motivated in Chapter II using a calibrated experimental environment with human subjects, and I briefly discuss my method for analyzing the experimental observations.

In Chapters IV, V, and VI, I discuss the experimental data and subsequent analysis in detail. Specifically, in Chapter IV, I provide an overview of the experimentation as performed and articulate my data coding schema. I also launch my analysis with statistical overviews of the experimental data. In Chapters V and VI, I explore the experimental data in greater detail, examining the main effects (Chapter V) and interaction effects (Chapter VI) suggested by my theoretical model (motivated in Chapter II). I close the dissertation with a high-level discussion of the results of my research in terms of its theoretical implications, and I make suggestions for future work generated by my experimentation.

H. SUMMARY

By way of further contribution, this work extends structural contingency theory to work groups through the lens of information processing (Galbraith 1973; Galbraith 1974; Daft & Lengel 1984; Daft & Lengel 1986; Egelhoff 1988; Egelhoff 1991; Gales et al. 1992) and knowledge sharing (Gupta & Govindarajan 1991; Birkinshaw et al. 2002; Nissen 2006) to longitudinally examine the putative effects on team performance. It explores the question: When undertaking a complex task requiring reciprocal interdependence, how do team information processing structures and knowledge sharing interact to influence performance cross-sectionally, over time, and subject to structural reconfigurations?

II. LITERATURE REVIEW

In the previous chapter, I noted that contemporary theorizing suggests the intersection of information processing, knowledge flows and structural contingency theorizing can be fruitfully synthesized to explain collective performance, particularly among work teams operating in contemporary, dynamic environments. In this chapter, I expand upon this theoretical synthesis by discussing, in turn, a) structural contingency theory, b) information processing theory, and c) knowledge flows theory. I explicitly integrate information processing structures, knowledge flows as contingency variable, and collective performance into a cogent theoretical model focused on teams as the primary level of analysis.

While discussing structural contingency theory, I address historical views of both contingency and structure, and I modernize these perspectives through a knowledge-based orientation of collective action. Indeed, contingency theory's enduring efficacy within organizational studies suggests it continues to prove a useful framework for exploring collective performance. However, recent theorizing grounded within knowledge-based views of the firm implies that some of contingency theory's core concepts—such as the structural dimensions of centralization, formalization, and differentiation—may require definitions (or, at the very least, operationalizations) more suited to viewing organizations via information-based and knowledge-based lenses. Drawing from the work of contemporary scholars, I modernize some of the dimensions here, as well as elucidate their relationship to other key contingency concepts—such as archetype, interdependence and coordination. Consistent with the contingent-theoretic tradition, I contextualize my primary phenomenon of interest—work teams—within complex, interdependent task environments common to contemporary work, and I revisit the implications of this contextualization throughout the literature review. Through merging developments within the three theoretical traditions with empirical evidence from prior studies—while maintaining contextual consistency of complex interdependent task environments—I create and differentiate the theoretical model from prior, related work of other scholars. In so doing, I arrive at several hypotheses at the team and

individual levels of analysis that require further investigation to support or refute. Short portions of the text are adapted from previous work (Leweling & Nissen 2007b).

A. STRUCTURAL CONTINGENCY THEORY

In this section, I briefly summarize some of the key tenets of structural contingency theory. Contingency theory has retained a central place in organization studies research for over half a century. Beginning with the seminal works by Burns and Stalker (1961), Woodward (1965), and Lawrence and Lorsch (1967a; 1967b), organization theory has been guided by the understanding that no single approach to organizing is best in all circumstances. Moreover, myriad empirical studies (e.g., Woodward 1965; Mohr 1971; Pennings 1975; Pennings 1987) have confirmed that poor organizational fit degrades performance, and many diverse organizational forms (e.g., Bureaucracy, see Weber 1947 translation; M-Form, see Chandler 1962; Clan, see Ouchi 1981; Network, see Miles & Snow 1978; Platform, see Ciborra 1996; Virtual, see Davidow & Malone 1992) and configurations (e.g., Machine Bureaucracy, Simple Structure, Professional Bureaucracy, Divisionalized Form, Adhocracy, see Mintzberg 1980) have been theorized to enhance fit across an array of contingency factors.

1. Knowledge Sharing as Contingency

Contingency factors vary widely in the literature (e.g., age, environment, size, strategy, technology), as have the frameworks supporting the contingency theory model (i.e., the classic, contemporary and hybrid approaches outlined in Chapter 1). In particular, task environment has proven an enduring contingency variable in the literature, and following Lawrence and Lorsch (1967a; 1967b), contingency theory has often emphasized *uncertainty* as critical dimension of task environment. Focus on task uncertainty in the contingency literature is not surprising, as its theoretical development has concurred with the rise of a general sentiment that powerful socio-economic factors—such as “post-industrial” economies (Bell 1976), increasingly globalized flows of goods and services (Castells 1996), and ubiquitous computing (Weiser 1993)—are shaping organizational life in unexpected and unprecedented ways (Barrett 1998), leading

to greater uncertainty in organizational undertakings and outcomes. Theoretical sources of task uncertainty have varied in the literature, but are often characterized along dimensions of task simplicity–complexity (Shaw 1951; Duncan 1972; McGrath 1984; Campbell 1988), task stability–dynamicism (Duncan 1972; Dess & Beard 1984), and task routineness-nonroutineness (Perrow 1967). In this theoretical framework, complex, dynamic, nonroutine tasks are posited to introduce greater uncertainty to organizational work than simple, stable, routine tasks.

Predictions about increasingly turbulent, chaotic, and uncertain environments on both macro and micro socio-economic scales are sometimes attributed to those loosely labeled as globalization or “information age” theorists (see e.g., Toffler 1980; Naisbitt 1982; Castells 1996; Ek 2000; Dunn 2002). The merits and demerits of their arguments are not debated here, but it becomes important to note that some of the overarching postulates advanced in this vein—1) task environments (particularly for organizations, organizational teams, and workers within organizations) are becoming increasingly turbulent and complex, 2) information and knowledge transactions are becoming an increasingly important basis of economic relationships, and 3) wealth can be generated by successfully leveraging information and knowledge rather than material assets—have echoes throughout the academic discourse. Whether such claims are sufficient for successfully arguing a fundamentally “new” economic order has arrived remains hotly debated, but on a less grandiose scale, at least some related hypotheses are achieving scholarly consensus.

Simon (1973), for example, describes a post-industrial world in which “organizational decision making ...shows every sign of becoming a great deal more complex than the decision making of the past” (p. 269). Similarly, Harris and Harris (1996) identify environmental uncertainty as the “fundamental reality” of contemporary work, and Sanchez (1997) argues that “the rapid development of major new technologies, the increasing globalization of markets, the rise of innovative new forms of organizations, and the appearance of new patterns of intense competition” (p. 71) are creating “unprecedented levels of environmental change and uncertainty for organizations of all types” (p. 71). Achrol (1991) perceives increasing environmental uncertainty as an

important trend affecting marketing organizations, while Lang and Lockhart (1990) describe how deregulation created environmental uncertainty in the airline industry. With task uncertainty located exogenous to organizations, many scholars have suggested knowledge—and more specifically, knowledge creation and transfer—as a source of sustainable competitive advantage for organizations operating within such environments (Drucker 1993; Blackler 1995; Argote & Ingram 2000).

One implication of such arguments is that if the contingency of environmental uncertainty (e.g., task complexity, task interdependence) is held constant, *knowledge creation and transfer should emerge as important contingency variables for predicting collective performance*, as Birkinshaw et al (2002) posit. Growing empirical studies and theorizing about the importance of knowledge creation and transfer within organizations and work groups (Walz et al. 1993; Nonaka & Takeuchi 1995; Janz et al. 1997; Rulke & Galaskiewicz 2000; Anand et al. 2003) support this view, but disjointed findings suggest that knowledge transfer as a contingency variable is underexplored and perhaps inadequately theorized. This gap leads to the theoretical model outlined in Figure 4 below in which collective performance is predicted by (as yet unspecified) structure interacting with knowledge sharing as contingency. This model is consistent with trends in contemporary contingency theorizing outlined in Chapter 1 (see Figure 1) in which structure is posited to interact with contingencies to influence performance, rather than contingency predicting structure.

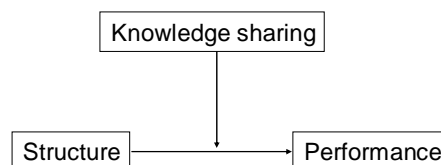


Figure 4. Knowledge Sharing as Contingency Variable

Birkinshaw et al's (2002) work uses a model similar to Figure 4 above in which knowledge is explicitly identified as a contingency variable. However, Birkinshaw et al (2002) hypothesize that certain characteristics of knowledge—which they identify as

observability (i.e., the extent to which knowledge can be replicated by the viewer of a process and/or outcome) and *system embeddedness* (i.e., the extent to which the knowledge is particularized to specific contexts)—predict organizational structures. In particular, Birkinshaw et al (2002) argue that observability and system embeddedness predict unit autonomy and interunit integration of 110 Swedish research and development subunits within 15 multinational firms.

Although Birkinshaw et al (2002) posit that knowledge characteristics predict performance, the causal direction of their findings appears ambiguous and suggests that a more contemporary view of contingency theorizing could be fruitful for explaining the relationship of knowledge sharing to collective performance. To address this causal ambiguity and consistent with views that emphasize knowledge flows (Gupta & Govindarajan 1991; Drucker 1993; Nonaka & Takeuchi 1995; Nissen & Levitt 2004) for creating competitive advantage, I have developed a simpler and more basic argument. My argument is grounded in the more contemporary view of structural contingency theory, positing that structure and contingency *interact* to influence performance. It stresses that *knowledge characteristics* are not necessarily useful predictors of structure. Rather, the argument stresses that *knowledge transfer* interacts with structure to predict performance. Put simply, I suggest that the capacity of teams to transfer knowledge *interacts* with existing work structures (i.e., information flows) to predict collective and individual performance. This theoretical model allows the transfer of knowledge between organizational agents to serve as a more relevant contingency consideration than specific attributes of agent-held knowledge.

This revamping of Birkinshaw et al's (2002) theoretical model provides another advantage: responding to criticism, particularly by strategic choice theorists (Child 1972; Jennings & Seaman 1994), that classic contingency theory imposes an untenable "structural determinism" (Westwood & Clegg 2003) in which management interventions (Covin & Slevin 1989; Doty et al. 1993), cultural factors (DiMaggio & Powell 1983; Zammuto & O'Connor 1992) and like variables hold little sway on how organizational work is structured. Focusing on how the *interaction of* knowledge sharing and structure predicts collective performance accommodates concepts such as equifinality (Doty et al.

1993; van de Ven & Poole 1995; Gresov & Drazin 1997), which asserts that various organizational configurations can produce relatively similar performance. This revamped theoretical model thus returns choice about how work is structured to organizational designers and re-designers—in many cases, strategic-level or unit-level managers—while still accommodating hypotheses that some organizational configurations may prove more adept within some task environments. Responding to various inputs and constraints, managers possess varying amounts of discretion to organize work structures (Haleblian & Finkelstein 1993); these work structures, combined with the contingent environments, are important predictors of collective performance (Child 1972; Child 1975; Miles & Snow 1978). Knowledge remains a contingency variable (Birkinshaw et al. 2002) in the theoretical model. However, in the model, knowledge as an objective entity becomes less important than *flows of knowledge* among organizational agents.

2. Structure: An Information Processing View

Structure, of course, is the companion theoretical construct to contingency in the structural contingency paradigm. Investigating team structure is not unknown within the team literature (Keck & Tushman 1993; Levitt et al. 1994; Urban et al. 1995; Urban et al. 1996; Keck 1997; Stewart & Barrick 2000). However, Hollenbeck et al (2002) suggest that theorizing about teams could benefit from more explicit extensions of structural contingency theory, particularly by extending the concept of fit to the team level of analysis.

When explored by scholars, team structure often refers to composition of its team members' attributes—such as demography (Keck 1997), experience (Rentsch & Klimoski 2001), diversity of skill (Walz et al. 1993), personality (Barrick et al. 1998) or heterogeneity of gender and race (Baugh & Graen 1997). Dimensions of organizational structure, however, are grounded less in the attributes possessed by the agents comprising the group and focused more on how the agents within the organization interact with each other. In the team literature, for example, structure might refer to the diversity of skills that each team member brings to the group. In the organizational literature, on the other hand, structure might refer to the allocation of decision rights about resources among

various organizational subcomponents. Although exceptions certainly exist, structure in the team literature often seems to refer to a characteristic that members bring *to* the team, while structure in the organizational literature refers to a characteristic imposed *upon* its subcomponents. These differences are not irreconcilable, but serve an important starting point for subsequent theorizing.

In the team literature, views based on dimensions of structure traditionally associated with the organizational literature—such as centralization, formalization, differentiation (Pugh et al. 1968) and interdependence (Thompson 1967)—are not prominent, although some important exceptions exist. Stewart and Barrick (2000), for example, use field methods to examine how interdependence and task environment influence team performance. Correspondingly, Wong and Burton (2000) build on Levitt et al.'s (1994) computational framework to argue that high performance in virtual teams requires increased emphasis on lateral communications. Other scholars incorporate concepts from the related organizational forms literature (see e.g., Miles & Snow 1978; Mintzberg 1980; Ouchi 1981; Davidow & Malone 1992), to explore how dimensions of hierarchy impact collective performance within work units (e.g., Argote 1982; Priem 1990; Hollenbeck et al. 1995; Urban et al. 1995). From an information-based perspective, scholars focused on top management teams have also found structural elements of team information processes as compelling factors for explaining performance (e.g., Hambrick & D'Aveni 1992; Haleblian & Finkelstein 1993). Thus organizational definitions of structure are not unknown to the team literature and appear to be gaining traction as a result of their explanatory power.

One of the central tenets of structural contingency theory posits that organic (i.e., adhocratic or “participatory”) organizational structures outperform in complex and dynamic task environments, while mechanistic (i.e., hierarchical) organizational structures outperform in stable and simple task environments (Burns & Stalker 1961; Tushman & Nadler 1978; Donaldson 2001). Interestingly, however, laboratory and field studies suggest that managers adopt countertheoretical approaches when faced with environmental turbulence (Bourgeois et al. 1978; Slevin & Covin 1997). Bourgeois et al (1978) attribute this reaction to a desire to reduce uncertainty by formalizing the

information processing structure when the organization encounters unexpected events. Formalization, however, serves as only one component of structure; other dimensions are also invoked to compare whether a particular organization or work group tends toward hierarchical (mechanistic) or participatory (organic) organizing.

In particular, differentiation, centralization, and formalization have achieved high levels of consensus as useful means for differentiating the two archetypes (Pugh et al. 1968; Hage et al. 1971; Dalton et al. 1980; Fry & Slocum 1984; Miller et al. 1991; Doty et al. 1993; Levitt et al. 1999; Daft 2001). Moreover, these three dimensions are often accompanied by discussion about task interdependence (Thompson 1967). Differentiation is often characterized as having both a vertical and horizontal components (Blau 1970; Van de Ven 1976; Dewar & Hage 1978; Fry 1982). When operationalized, horizontal differentiation often refers to the number of departments within an organization, while vertical differentiation often refers to the number of supervisory levels. This work makes most use of the structural variation based on vertical differentiation. Consistent with early communication studies (e.g., Bavelas 1950; Leavitt 1951; Guetzkow & Simon 1955) and contemporary operationalizations of information processing theory (Levitt et al. 1994; Levitt et al. 1999), centralization refers to the tendency of an organizational agent to interact more often with superiors than peers. Formalization, as described above, refers to rules and procedures that structure interactions among organizational agents.

Structural dimensions can be defined using a number of theoretical concepts as the undergirding basis (e.g., power, authority, resource allocation), but recent scholarship (e.g., Levitt et al. 1994; Wong & Burton 2000) suggests that the information processing lens is particularly informative for exploring team performance. Viewed in this way and consistent with the descriptions above, one can define core dimensions of *information processing structure* as:

- Centralization – level of authority required to share information across the team and whether information queries are forwarded to peers or superiors (Malone 1987; Kunz et al. 1998; Daft 2001)

- Formalization – extent to which rules and procedures define and reinforce differentiated team member roles and vertical levels (Reimann 1973; Walsh & Dewar 1987; Daft 2001),
- Lateral differentiation – specialization of the information processed by team members and heterogeneity of team member functions (Blau 1970; Reimann 1973; Fry 1982; Lawrence & Dyer 1983; Blau 1995)
- Vertical differentiation – number of vertical levels within the team (Blau 1970; Reimann 1973; Fry 1982; Lawrence & Dyer 1983; Blau 1995)
- Task interdependence – level of interaction required among team members to perform the task, as well as dependence of team member’s output on actions of others (Wageman 1995; Kozlowski et al. 1999; Katz-Navon & Erez 2005).

The definitions outlined above invoke subtle, but important, distinguishing characteristics for operationalizing typical dimensions of organizational structure. Specifically, the definitions derive from the work of Galbraith (1973; 1974), Tushman and Nadler (1978), and Levitt and colleagues (Levitt et al. 1994; Jin & Levitt 1996; Kunz et al. 1998) to more explicitly define organizational structure via an information processing lens, and they are also consistent with extending the information processing framework to a knowledge-based view of the firm (Grant 1996a; Grant 1996b; Spender & Grant 1996; Spender 1996). These distinctions are neither semantic nor prosaic, as Grant (1996b) contends that the knowledge-based view of the firm requires adjusting scholarly emphasis from cooperation to coordination as a primary construct for describing the means through which (i.e., “how”) productive output is achieved.

Briefly, these definitional changes shift scholarly focus from authority relationships and creating goal congruence to knowledge transfer relationships and creating mechanisms for integrating knowledge-based activities (Grant 1996b; Spender 1996; Nonaka et al. 2000). In so doing, knowledge-based views of the firm consider knowledge not as an objective resource per se, but rather view knowledge *sharing* as a process for creating competitive advantage (Spender 1996). Table 2 briefly summarizes some of the differences between resource and knowledge-based views of the firm, and it should be noted that differences between the perspectives are neither wholly complete

nor entirely orthogonal. Rather, the differences represent a change of emphasis: knowledge-based views focus more explicitly on information and knowledge structures while resource-based views focus more explicitly on authority structures. The differences also respond to Simon's (1973) call to focus organizational inquiry more clearly on information processes, and is consistent with his contention "in the post-industrial society, the central problem is not how to organize to produce efficiently ... but how to organize to make decisions—that is, to process information" (p. 269-70).

	View of the firm	
	<i>Resource-based</i>	<i>Knowledge-based</i>
Motivational problem	Cooperation	Coordination
Primary theoretical constructs	Authority relations Control mechanisms	Knowledge transfer Knowledge integration
Organizational purpose	Reconcile and subordinate disparate goals of members	Create mechanisms to integrate individual's specialized knowledge
Productive resource	Varies	Knowledge
Ownership of productive resources	Stockholders	Employees
Definitions of organizational structure		
<i>Centralization</i>	Level of hierarchy with authority to make a decision regarding resource allocation	Level of authority required to transfer information
<i>Formalization</i>	Extent to which rules and procedures define and reinforce differentiated roles and vertical levels	Extent to which rules and procedures define and reinforce differentiated roles for processing and transferring information
<i>Lateral differentiation</i>	Diversity of occupational positions; number of departments or divisions	Level of specialization of the information processed based on occupational position or assigned department
<i>Vertical differentiation</i>	Number of supervisory levels	Number of supervisory levels
<i>Task Interdependence</i>	Level of interaction required to perform task; dependence of individual output upon actions of others	Level of interaction required to perform task; dependence of individual output upon actions of others

Table 2. Resource and Knowledge-based Views of the Firm⁴

⁴ This table represents a synthesis of numerous scholars (Reimann 1980; Walsh & Dewar 1987; Blau 1995; Wageman 1995; Grant 1996b; Kozlowski et al. 1999; Daft 2001; Miner 2002; and Katz-Navon & Erez 2005).

B. THEORETICAL MODEL

Viewed through an information- and knowledge-based lens, structural contingency theory takes a more modern, contemporary form that is informed by emerging theorizing on organizations as information processing systems (Galbraith 1973; Galbraith 1974; Tushman & Nadler 1978) and knowledge as an important contingency variable (Birkinshaw et al 2002; Hutzschenreuter & Listner 2007) for explaining collective performance. Key dimensions of structure—such as centralization, formalization and vertical differentiation—transform in a straightforward manner to this new epistemological lens and are explicitly operationalized in numerous studies (Levitt et al. 1994; Jin & Levitt 1996; Kunz et al. 1998; Wong & Burton 2000). Yet as Birkinshaw et al (2002) and others (Nonaka & Takeuchi 1995; Rulke & Galaskiewicz 2000; Anand et al. 2003; Argote et al. 2003) have suggested, differences in information processing structures are insufficient to explain variance in collective performance, and knowledge flows emerge as an underexplored contingency variable. Through explicitly defining information processing structure and contingent knowledge sharing—and by arguing that contingent knowledge sharing represents a moderating, not mediating, relationship between structure and performance—the basic theoretical model undergirding this research takes form and is illustrated within Figure 5 below.

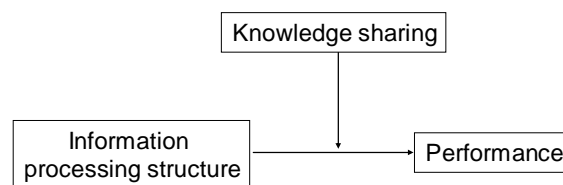


Figure 5. Theoretical Model

C. RELATED CONCEPTS

In order to provide greater clarity about the bounds of the theoretical model as well as the model's relationship to other key terms in the contingency theory literature, I

briefly discuss the concepts of archetype, interdependence, and coordination below. I also discuss the relationship of this work to the network organizations literature.

1. Relationship Between Structure and Archetype

Drawing from Mintzberg's (1980) characterization of five archetypal organizational forms, Nissen and others (Nissen 2005b; Orr & Nissen 2006; Gateau et al. 2007; Leweling & Nissen 2007b) have suggested that it is possible for dimensions of organizational structure to define a formal organizational design and trade space. Further, Gateau et al (2007) suggest that various points within this design space (e.g., low centralization, moderate formalization, high differentiation) could represent archetypal organizational forms, a view consistent with Doty et al's (1993) field work in which organizations were categorized by their relative similarity to Mintzberg's (1980) archetypal forms. By examining relative performance of the archetypal forms when undertaking similar tasks, Gateau et al (2007) argue, notions of fit can be rapidly explored through computational models and simulations. Furthermore, differentiating the forms through dimensions of organizational structure enables researchers to explicitly differentiate among organizational archetypes; in essence, the archetypes become defined by their relative positions along these continua.

a. Comparing Edge and Hierarchy

For example, within this design space, Nissen and colleagues (Nissen 2005b; Orr & Nissen 2006; Gateau et al. 2007) define *Hierarchy* organizations as possessing high centralization, high formalization and high differentiation, while *Edge* organizations operate at the opposite end of the design space, possessing structural characteristics of low centralization, low formalization and low differentiation. It should be noted that points along these dimensions are not absolute, but rather important in relative terms—i.e. centralization within a Hierarchy is higher than within an Edge organization, formalization within a Hierarchy is higher than within an Edge organization, and so on. Some comparative characteristics between Edge and Hierarchy are captured in Table 3. The focus on centralization, formalization and vertical

differentiation is consistent with Dalton et al's (1980) argument that these dimensions are critical for understanding the relationship between organizational structuring and collective performance, and Reimann's (1973) work suggesting that the factors are analytically unique.

		Archetype	
		<i>Hierarchy (mechanistic)</i>	<i>Edge (organic)</i>
Structural Dimension	<i>Centralization</i>	High	Low
	<i>Formalization</i>	High	Low
	<i>Vertical differentiation</i>	High	Low

Table 3. Organizational Form vs. Structural Dimension (adapted from Gateau et al. 2007; Orr & Nissen 2006)

b. Comparing Edge to Mintzberg's Archetypes

While the Edge organization relates, in part, to the organic structures of Burns and Stalker (1961), Nissen and colleagues (Nissen 2005b; Orr & Nissen 2006; Gateau et al. 2007; Nissen 2007a) ground the Edge construct firmly within the organizational archetypes literature (Mintzberg 1980; Doty et al. 1993). Drawing upon Alberts and Hayes' (2003) concept of the Edge organizations as emphasizing peer-to-peer relationships within a setting of high goal congruence and dynamic allocation of resources, Nissen (2007a) and colleagues (Gateau et al. 2007) describe the Edge as a hybrid of Adhocracy, Professional Bureaucracy, and Simple Structure. Specifically, Nissen (2007a) and others suggest that Edge structures reflect a mix of characteristics commonly identified with other organizational archetypes – such as mutual adjustment (i.e., Adhocracy), low vertical differentiation (i.e., Professional Bureaucracy) and low formalization (i.e., Simple Structure). This firm grounding assists to refine our understanding of the Edge form relative to other longstanding organizational archetypes (i.e., Mintzberg 1980; Doty et al. 1993). In turn, the Edge archetype can then be compared against others not only relative to specific design characteristics (particularly structural elements, such as centralization, formalization, and vertical differentiation), but also relative to performance under various contingent-theoretic conditions.

2. Interdependence

Task interdependence is deliberately excluded from Table 3, as there exists some debate within the literature about whether task interdependence is an attribute of the task or whether task interdependence is an attribute of how work is subdivided and assigned in order to accomplish the task. In practice, Thompson (1967) points out, interdependencies are created from both sources—sometimes the task is defined in such a way that the task itself requires interdependence among the organizational agents, sometimes the organizational agents arrange their work relationships in a manner that creates more interdependence than others, and sometimes both concur. Thompson (1967) observes that internal work units commonly display *reciprocal interdependence*, in which organizational agents continuously exchange expertise and resources. Regardless of source, however, interdependencies introduce uncertainty (Thompson 1967; Galbraith 1974; Tushman 1979; Janz et al. 1997), leading Galbraith (1973; 1974) to prescribe work arrangements that reduce interdependencies (regardless of the assigned task characteristics) to create higher performance. Tushman and Nadler (1978) concur, suggesting that task complexity, task unpredictability and reciprocal interdependence introduce uncertainty for organizations. Strategic choice theorists, however, stipulate that such arrangements may prove unrealistic when linked to managerial constraints (e.g., Ring & Perry 1985)—ordering work sequentially, for example, may take more time than project constraints allow.

From an information processing perspective, Thompson's (1967) categories of interdependency relate to the source of any given organizational agent's *information inputs*. As an instantiation, one can imagine a scenario in which the information needed to resolve a given task arrives from 20 external sources to 10 different organizational agents simultaneously. In this scenario, the nature of the task introduces a certain amount of interdependence, as the information required to resolve the task “enters” the organization at 10 unique nodes. However, the agents may now choose how to structure the information flows for combining these 20 “pieces” of information. Thompson's (1967) *pooled* interdependence would suggest that each of the 10 organizational agents processes each of the 20 pieces of information independently, then passes the information

along to some external recipient to resolve the task. With pooled interdependence, there is no need for the agents to interact with one another; each can process his or her information independent of actions by others. *Sequential* interdependence would suggest that the 10 agents process the information in some pre-specified order, with each agent waiting for a previous agent to process his or her information prior to processing his or her own—a sort of information assembly line. *Reciprocal* interdependence, however, would suggest that the 10 agents process the information via a complex web of information sharing relationships, perhaps even needing to exchange information beyond the 20 “inputs” in order to produce the task “output.” Given this example, Galbraith (1973; 1974) would suggest that pooled interdependence introduces the least interdependence (and hence least complexity) into the work, while reciprocal interdependence introduces the most interdependence (and hence greatest complexity) of Thompson’s (1967) taxonomy. Sequential interdependence would fall somewhere between the other two types.

Returning to the example, suppose that the information required to resolve the task emanated from only five (as opposed to 20) external sources at the outset, and that this information was received by two (as opposed to 10) organizational agents. In this case, external characteristics of the task (information is received from 5 vs. 20 external sources, moreover, the information is received by 2 vs. 10 organizational agents) result in a task that is less interdependent (and hence less complex) from the outset. By way of this simple example, task interdependence emerges a somewhat awkward and thorny concept, as it becomes unclear whether the interdependence derives from external inputs or internal work arrangements, as Thompson noted (1967). For the purpose of this work, distinguishing work structures via the dimensions of centralization, formalization and vertical differentiation provides a cohesive and cogent means for considering organizational information processing. To enhance clarity and consistency, task interdependence is viewed as an immutable factor that exists *externally* to the *pre-existing* work structure. More specifically, task interdependence is considered *as a function of the level of interaction reasonably required to accomplish a task*. For this work, then, task interdependence relates fundamentally to the initial distribution of

information inputs to organizational agents involved. It assumes that this initial distribution of information is inflexible, that the received information inputs are important to completing the task, and that the agents must share these information inputs in order to complete the task successfully.

3. Coordination

Interdependence, particularly viewed via an information processing lens, relates directly to Grant's (1996b) assertion that knowledge-based views of the firm require scholarly emphasis on coordination (i.e., information relationships) over cooperation (i.e., authority relationships). Grant's (1996b) view is consistent with scholars who argue that the structure of information flows represents a cogent means for operationalizing organizational coordination (e.g., Hage et al. 1971) when organizations are viewed via an information processing lens. To the extent that these information processing structures can be coherently differentiated from others, taxonomies of coordination emerge. Mechanisms of coordination, in turn, form part of the basis for differentiating organizational forms (1980).

As Thompson (1967) hypothesized, empirical work suggests that the coordination strategy of mutual adjustment, which Mintzberg (1980) associates to adhocracies and Gateau et al (2007) have operationalized in structural terms very similar to *Edge* organizations (i.e., low centralization, low formalization and low differentiation), results in higher performance in complex or uncertain task environments, but lower performance in simple and stable environments (Baumler 1971; Reeves & Turner 1972; Argote 1982). For example, Baumler's (1971; see also Miner 2002) laboratory experimentation with decision making organizations suggests that formalized and structured control is useful in task settings with minimal interdependence (i.e. low complexity), while informal and unstructured control allows proves fruitful in task settings with extensive interdependence (i.e., high complexity). Following Woodward's (1965) seminal field work, Reeves and Turner (1972) concur, suggesting that "mutual adjustment could ... be appropriate in a number of situations of high uncertainty or complexity" (p. 96). However, Reeves and Turner (1972) also warn that the appropriate level of analysis for exploring coordination

is individual work units, not organizations as a whole. Argote's (1982) field work on hospital emergency units also seems to support this view, as work units with high formalization outperformed in environments with low uncertainty, while work units with low formalization outperformed in environments with high uncertainty. These studies, however, emphasize structure and coordination undergirded by authority, not information, relationships so it remains an open empirical question whether the postulates hold in more contemporary, "knowledge-based" views of the work units. Contemporary computational work (e.g., Levitt et al. 1994; Wong & Burton 2000; Gateau et al. 2007) suggests that such postulates will prove enduring when operationalized via an information processing lens, and field studies are promising (e.g., Daft & Macintosh 1981; Looney & Nissen 2006).

4. Relating Edge Structures and Network Organizations

Since its inception in the literature, scholars have struggled to integrate the concept of network organizations—and more aptly network organizing—into the larger body of organizational studies literature at the individual (e.g., Granovetter 1973), group (e.g., Krackhardt & Hanson 1993), organizational (e.g., Raider & Krackhardt 2002) and interorganizational (e.g., Ghoshal & Bartlett 1990; Baker & Faulkner 2002) levels of analysis. A definitional consensus of the phenomenon appears to be emerging, with Borgatti and Foster (2003) describing network organizations as an organizational form “characterized by repetitive exchanges among semi-autonomous organizations that rely on trust and embedded social relationships to protect transactions” (p. 995) and Podolny and Page (1998) defining a network form of organization as “any collection of actors ($N \geq 2$) that pursue repeated, enduring exchange relations with one another and, at the same time, lack a legitimate organizational authority to arbitrate and resolve disputes that may arise during the exchange.” (p. 59) Borgatti and Foster (2003), however, suggest that “while there is general agreement on the benefits of [the network organization as a] ... new organizational form, its ontological status remains somewhat unclear” (p. 995). Specifically, Borgatti and Foster (2003) question whether identifying networks as a new organizational form is necessary for the types of research questions to which network-

oriented (especially graph-theoretic, see Wasserman & Faust 1994) analyses seem best suited. In describing the disjointed state of the network organization literature, Borgatti and Foster (2003) continue:

...It does not help that “network organization” can refer to a logic of governance, a collection of semi-autonomous firms, or an organization with “new” features such as flat hierarchy, empowered workers, self-governing teams, heavy use of temporary structures (e.g., project teams, task forces), lateral communication, knowledge-based, etc. Adding to the linguistic chaos, some authors call these organizational forms “networks” and pronounce that, in the 21st century, firms must transform themselves from organizations into networks, confusing those who think of organizations as already consisting of networks. With all of this, it is perhaps no surprise that studies of network organizations have generated ‘diverse, varied, inconsistent, and contradictory’ findings. However, attempts to bring order to this area continue. (pp. 995-6)

To the extent, then, that the literature refers to network organizations in the vein of an organizational form with features such as flattened work structures, self-governance, and reliance on lateral, peer-to-peer communications (Bush & Frohman 1991; van Alstyne 1997; Ishida & Ohta 2001), network organizations provide a clear parallel to organic organizational structures (Burns and Stalker 1961; Tichy & Fombrun 1979; Tichy et al. 1979; Bovasso 1992) and Edge organizations (Orr & Nissen 2006; Gateau et al. 2007; Nissen 2007a).⁵ However, other interpretations of network organizations used throughout the literature, such as networks serving as governance mechanisms within organizations (e.g., Jones et al. 1997), hold fewer direct parallels with the theoretical model developed in this chapter, creating complications for cogent interpretation of the results via a network organization lens.

Viewing the results of this work within the network organization concept thus requires careful theoretical alignment with the paradigmatic tradition of identifying certain elements of structure (e.g., “flatness,” emphasis on peer-to-peer communications)

⁵ Further, when such organizations reflect temporary constellations of persons with variegated knowledge, Hedlund (1994) suggests calling such structures “N-form” corporations.

as key characteristics of network organizations. When this network organization paradigm is used, clear parallels exist. Cogently integrating the full body of network organization theory beyond a superficial glancing is beyond the scope of the work presented here (for a review of the network paradigm within organizational research, see Borgatti & Foster 2003). Doing so, however, could offer the potential of clarifying at least some of theoretically posited relationships between task contingencies and network organizations (cf. Pearce & David 1983; Shrader et al. 1989; Topper & Carley 1999), in addition to offering an alternate motivational framework for exploring concepts of organizational and team structure. Integrating network organizing concepts with the Edge form is thus suggested as a topic for future research.

D. INFORMATION PROCESSING THEORY

Although scholars argue that knowledge-based theories of the firm are incomplete (e.g., Grant 1996b; Spender 1996; Nonaka et al. 2000), the information processing paradigm on which they rest is well developed within academic discourse. In particular, the work of numerous scholars (Galbraith 1973; Galbraith 1974; Tushman & Nadler 1978; Tushman 1979; Levitt et al. 1999), which translates well-understood dimensions of organizational structure to the information processing framework and operationalizes them into useful constructs, is a powerful development for theorizing about organizational design. These advances are particularly useful to the extent that such operationalizations bridge field, computational and laboratory studies (Nissen et al. 2004; Leweling & Nissen 2007b) and thus contribute to “full cycle” organizational theorizing (Chatman & Flynn 2005).

Stated briefly, information processing theory views organizations as collective decisionmaking systems (March & Simon 1958) in which the processing of information serves as the primary locus of activity (Tushman & Nadler 1978). Bounded rationality (Simon 1957; Simon 1997) suggests that organizational agents have limited capacity for processing information, leading scholars to argue that organizations that structure their information processing functions more efficiently will outperform organizations with less efficient information processing structures (Radner 1993; Keller 1994; Rogers et al.

1999). Moreover, some scholars (Drucker 1993; Grant 1996a; Child & McGrath 2001; Kellogg et al. 2006) argue that contemporary macroeconomic shifts emphasize the imperative for organizing information processing structures efficiently as information (and knowledge) flows, not material flows, serve as the primary productive output of organizations.

Tushman and Nadler (1978) identify core assumptions that serve as the epistemic underpinnings of information processing theory. They argue, for example, that inherent within the information processing view is an open systems perspective of organizing in which one of the primary functions of collective action is to reduce environmental uncertainty through efficient and cogent processing of information. As a result, the basic unit of analysis becomes the organizational *subunit*, suggesting that the information processing perspective *holds particular utility for exploring work groups*. Tushman and Nadler (1978) also suggest that task complexity and task interdependence are two critical factors to consider when assessing “fit” between a collective’s information processing structure and task environment. Specifically, routine tasks with minor levels of intra-unit interdependence should require minimal information processing. However, tasks that are complex, dubitable or involve high levels of interdependence are “associated with greater uncertainty” (p. 615) and thus create requirements for high levels of information processing. In latter task environments, Kellogg et al (2006) concur, suggesting that adaptation and horizontal collaboration will represent the core competencies of firms rather than specialized routines (p. 22). This theorizing implies that low differentiation and low formalization of information processing functions should be associated with higher collective performance, particularly when tasks are complex. A summary of Tushman and Nadler’s (1978) concept of fit within the information processing paradigm is highlighted in Table 4 below.

		Uncertainty	
		<i>Low</i> <i>[Routine, simple task in stable environment]</i>	<i>High</i> <i>[Non-routine, complex task in dynamic environment]</i>
Information processing requirements	<i>Low</i>	Fit	Misfit
	<i>High</i>	Misfit	Fit

Table 4. Information Processing Fit (adapted from Tushman & Nadler 1978)

Information processing theory thus suggests that organizations with information processing structures that more adequately fit their task characteristics and task environments should benefit from greater efficiencies—leading, over time, to higher performance.

1. Performance

Seminal studies by Bavelas (1950), Leavitt (1951), Guetzkow and Simon (1955), and others (Cyert et al. 1961)—which have been described alternatively as atheoretical (Wasserman & Faust 1994) or so integrative that theory and empirical research are indistinguishable (Miner 2002)—form a core part of the empirical lineage for information processing theory. Researchers have thus long suggested that information flows form structures that predict collective performance. Moreover, contemporary studies buttress these early findings (Smith et al. 1991; Smith et al. 1994; Keller 1994; Monge & Contractor 2003). Merging early communication studies with the contingency theory paradigm (Lawrence & Lorsch 1967a; Lawrence & Lorsch 1967b; Thompson 1967) and restating dimensions of work structure in information processing terms begins to remedy the atheoretical nature of this early work. Moreover, the intersection of these theoretical lenses allows us to reconsider the importance of Burns and Stalker's (1961) distinctions between organic and mechanistic structures for contemporary work groups. A fresh view of Burns and Stalker's (1961) archetypes, then, would ask *from an information processing perspective*, which structure—mechanistic or organic—yields higher performance?

The question is not entirely without answer in the existing literature. Burns and Stalker (1961), for example, suggest that organic structures will prove more suited to

complex, dynamic environments, and mechanistic structures will prove more suited to simple, stable environments. Moreover, Galbraith (1973) argues that to cope with the contingency of environmental complexity and dynamicism (Duncan 1972)—two factors comprising environmental uncertainty—organizations seek to reduce their information processing needs and improve their information processing capacity (Premkumar et al. 2005). Such postulates lead to the following hypotheses, which require empirical testing:

- *Hypothesis 1:* In complex and interdependent task environments, Edge teams will outperform Hierarchy teams
 - *Hypothesis 1a:* Similarly, when assigned complex and interdependent tasks, individuals working within Edge teams will outperform individuals operating within Hierarchy teams
- *Hypothesis 2:* In complex and interdependent task environments, transforming from an Edge to Hierarchy structure, and vice versa, will influence team performance

2. Learning

Although myriad variables have long been associated with collective learning, only recently has the relationship between work structure and learning become explicitly tested within the organizational and teams literature (see e.g., Devadas Rao & Argote 2006). Some views of organizational learning suggest that collective learning involves “encoding inferences from history into routines that guide behavior” (Levitt & March 1988 p. 320), which suggests that organizations or teams with higher levels of formalization may demonstrate higher levels of learning than peers with lower levels of formalization. Less specifically, Shrivastava (1983) suggests that the organizational process of learning is influenced by “social, political and structural variables” (p. 17), but unfortunately, Shrivastava (1983) does not explicitly articulate the structural dimensions of organizational life that influence learning. Computational studies (e.g., Carley 1992) indicate that work groups with Edge characteristics may learn more quickly than work groups with Hierarchical characteristics, but her studies also indicate that turnover of personnel may dampen learning within Edge groups more than within Hierarchy groups.

Devadas Rao and Argote (2006) empirically examine the relationship between turnover and structure using human subjects within a laboratory setting, but an explicit test of structure and learning when turnover is *not* a primary consideration remains necessary. Interestingly, Romme (1996) suggests that in practice, both types of organizing are required to maximize collective learning, with Edge-like groups creating and understanding “novel information” (p. 411) and Hierarchy groups providing capacity for “processing and storing important learning results” (p. 411). Huber (1991) links information processing with collective learning, but does not explicitly link structure (e.g., centralization, formalization, differentiation) to the phenomenon. The lack of a coherent research stream that tests the relationship of information processing structures to learning suggests that testing such interactions could prove beneficial, which is reflected in the following hypothesis:

- *Hypothesis 3:* In complex and interdependent task environments, Edge teams will learn more quickly than Hierarchy teams
 - *Hypothesis 3a:* Similarly, when assigned complex and interdependent tasks, individuals working within Edge teams will learn more quickly than individuals operating within Hierarchy teams

3. Relationship to Sensemaking

Information processing does not refer strictly to Shannon’s (1948a; 1948b) model of information transfer or derivative models within information theory. While Miller’s (1956) model of information processing views human operators as communication channels capable of sending, storing, and receiving information, Tushman and Nadler (1978) explain that information processing and data processing are not synonymous. Following Galbraith (1973; 1974), organization information processing becomes a rubric for innumerable activities undertaken as humans interact with sensory data on both individual and collective levels, such as interpreting (Daft & Weick 1984) and sensemaking (Starbuck & Milliken 1988; Gioia & Chittipeddi 1991; Weick 1993a).

At both the individual and collective levels, sensemaking, literally the “making of sense” (Weick 1995), is retrospectively oriented toward the decisions preceding it (Weick

et al. 2005). Taylor and Van Every (2000) describe sensemaking as “a way station on the road to a consensually constructed, coordinated system of action” (p. 275, as cited in Weick et al. 2005), and as such, sensemaking is socially constructed, becoming entwined with the social and organizational structures (static view) and structuration (dynamic view) in which the sensemaking occurs (Gioia & Chittipeddi 1991; Weick 1993a; Maitlis 2005). Structures of social relations, organizational roles and meaning systems (Gioia & Chittipeddi 1991; Weick 1993a; Hill & Levenhagen 1995), individual and collective identity and image (Gioia & Thomas 1996), as well as cues, frames and triggering conditions (Starbuck & Milliken 1988; Griffith 1999; Maitlis & Lawrence 2007) derived from a dynamic, emerging situational contexts (Patriotta 2003; Weick et al. 2005) serve as core contributors to sensemaking processes, influencing, at the organizational level, strategy development (Schneider 1997) and organizational performance (Thomas et al. 1993; Raes et al. 2007). Artifacts of sensemaking—in particular, the behaviors (i.e., actions) enabled by sensemaking—are often readily observable, and many scholars observe the construction of sense (e.g., Gioia & Chittipeddi 1991; Patriotta 2003) in action. Actions enabled by sensemaking vary considerably, but at the micro-organizational level, however, one of the most basic observables is the decision about whether information is shared (or withheld) from others as individuals conjoin on a complex task (Kidwell & Bennett 1993; Byström & Järvelin 1995).

Starbuck and Milliken (1988) describe sensemaking as placing sensed data (i.e., stimuli) into a cogent framework of reference (see also Weick 1995, p. 4), which in some respects parallels the process of creating information by contextualizing data (Nonaka 1994; Nissen 2006). To the extent that sensemaking involves contextualizing (and creating a context for) environmental cues, then, sensemaking and information creation seem to describe similar human actions, and indeed, *creating information via contextualization of environmental inputs may serve as an abstract case of successful sensemaking*. Weick’s (1993a) classic study of the Mann Gulch disaster, as well as Snook’s (2002) exploration of the shutdown of two Blackhawk helicopters by friendly fire (see also Nissen et al. 2004), however, remind us that the *collapse* of sensemaking involves inadequate contextualization of sensed data, due to existing routines and/or

meaning systems offering little to no capability for reducing ambiguity given the current environment— i.e., the data exist, but they are not processed (i.e., contextualized) into information.

Although well beyond the scope of the work presented here, this discussion relates, in part, to the philosophical debate embodied within Simon's (1947 / 1976) *Administrative Behavior*. Cohen (2007) describes Simon's interpretation of rationality as "selecting the most appropriate means for achieving currently preferred ends" (p. 504), implying that sensemaking —however bounded in scope—occurs *prior to action*. Cohen (2007) further describes Simon's articulation of Dewey (1922 / 1988; 1938 / 1991, both as cited in Cohen 2007) as progenitor as highly ironic, as "Simon's directional hierarchies of ends and means, and clean separation of fact and value are exactly the perspectives that Dewey critiqued as he argued for a more situated and reflexive understanding of how thought, emotion, and habit interact with each other to produce —and be produced by— action." (p. 505) Following Simon and others, rational choice theorists would thus suggest a model in which sensemaking occurs, a proposed action is formulated, the action is implemented, and then the emergent situation (presumably, modified by the implemented action) is assessed. As Cohen (2007) points out, this epistemic stance is inconsistent with arguments by Dewey (1922 / 1988; 1938 / 1991) and Weick (1995) in which *action* precedes understanding and moreover, prior action creates triggers to influence future action.

Weick (1995), however, is adamant in his stance that sensemaking is retrospective in nature—i.e. that humans "make sense" of their actions only after the action is taken. Weick (1995) expresses his stance is partly inspired by conversations with Garfinkel (1967, as cited in Weick 1995, see pp. 10-11) about Garfinkel's work with jury deliberations—in which Garfinkel concludes that juries determine desired outcome well before determining harm or assigning blame. Thus to the extent that creating information refers to contextualizing retrospectively sensed data, scholars invoking concepts of sensemaking and information processing appear to be describing somewhat similar phenomena. To the extent that knowledge enables *future* action while sensemaking created understanding of *past* action and influences future action, however,

the undergirding epistemic stances of sensemaking, information processing, and knowledge flows theorizing begin to diverge, requiring careful caveats when linking the theoretical traditions together.

E. KNOWLEDGE FLOWS THEORY

Nonaka (1994) critiques the organizational information processing paradigm as projecting an unduly “passive and static” (p. 14) view of organizations, one in which organizations are viewed narrowly as input-process-output puzzle solvers. Instead, he argues, organizations dynamically create both information and knowledge as they undertake problem-solving, and it is through an ability to transfer this knowledge among organizational parts that organizations succeed in accomplishing complex, creative tasks—such as innovation. More specifically, he argues that within organizations, knowledge creation results from the “continuous dialogue between tacit and explicit knowledge” (p. 14) undertaken by organizational members, and identifies four types of knowledge creation: 1) socialization (tacit to tacit), 2) externalization (tacit to explicit), 3) internalization (explicit to tacit) and 4) combination (explicit to explicit). For the purpose of this dissertation, I concentrate on *combination*, or the transfer of explicit knowledge to explicit knowledge, which Nonaka (1994, p. 19) specifies as rooted within information processing theory.

Nonaka (1994) suggests that the meaning of terms such as “information” and “knowledge” are undergirded by the epistemic stance of the individual invoking these symbols. In his view, information consists of a “flow of messages” (p. 15), while knowledge becomes the “justified true belief” enabled by available information. Thus information provides context and meaning—enabling interpretation, but knowledge provides belief and anchoring, enabling action (see also Nissen 2006). Table 5 summarizes these differences.

	Information	Knowledge
Provides	Context and meaning	Anchoring and belief
Enables	Interpretation	Action

Table 5. Information versus Knowledge (adapted from Nonaka 1994; Nissen 2006)

Although many scholars argue a theoretical distinction between information and knowledge, operationalizing the difference between information and knowledge into cogent theoretical constructs (Bagozzi & Phillips 1982; Kerlinger & Lee 2000) sometimes presents practical problems. What constitutes information in one context may be construed as knowledge in another, depending upon the subjective and contextually-situated viewpoint of the user of information and knowledge. Nonetheless, Nonaka's (1994) and Nissen's (2006) distinctions of knowledge as enabler of action allow for numerous, albeit simplistic, distinctions to emerge: lists of objects and actions, for example, would reflect information in the same context in which utilizing or applying such lists would reflect knowledge. Robert's Rules of Order, for example, reflect information about a manner in which formal meetings might be structured, while decisions about whether to adhere to or deviate from Robert's Rules in a particular setting reflect knowledge. Even in this simple example, we note a continuous interplay between information and knowledge. The information about Robert's rules exists, remaining stagnant and persistent. Deciding about whether to follow Robert's rules, however, is an unrelenting task and requires combining information not only about Robert's Rules, but also continuously updated information about the current setting. Only through combining both information and knowledge is an individual able to determine whether Robert's rules are applicable to the given situation *right now*. Information enables the meeting participant to interpret and understand the context in which he finds himself; knowledge enables the meeting participant to determine what action to take next.

Walz et al (1993) point out that in complex knowledge-based work such as software design, individuals rarely possess all knowledge necessary to complete the assigned task and hence must either acquire or create knowledge in order to perform successfully. Eppler and Sukowski (2000) concur, arguing that team leaders must create

adequate knowledge transfer processes to facilitate high team performance. Since knowledge creation occurs at the individual level and knowledge is then transferred to larger groups (Nonaka 1994; Grant 1996a; Grant 1996b) capable of storing and accumulating it (March 1991), we would expect teams that share both knowledge and information to outperform those that share only information. We would also expect that individuals operating within teams that share both knowledge and information would outperform individuals operating within teams that share only information. These postulates appear to particularly benefit situations in which the task environment is highly uncertain (Galbraith 1974; Galbraith 1977) due to the task having characteristics of nonroutineness (Perrow 1967), complexity (Campbell 1988), and interdependence (Thompson 1967). However, the postulates could also clearly benefit from empirical analysis in a laboratory setting as a complement existing field work. These postulates lead to the following hypotheses:

- *Hypothesis 4:* In a complex and interdependent task environment, knowledge sharing improves team performance
 - *Hypothesis 4a:* Similarly, when assigned complex and interdependent tasks, individuals operating in teams that regularly share knowledge will outperform individuals operating in teams that do not share knowledge

Evidence of learning is often operationalized as improvement in observed performance over time, sometimes captured in learning curves (Argote 1999). As Argote et al (2003) have commented, collective learning, individual learning and knowledge management are linked through a number of theoretical traditions—including cognition, psychology, information systems, economics, and others. Argote et al (2003) caution, however, that a growing tendency to fragment research applicable to the two disciplines of organizational learning and knowledge management runs “the risk of propagating a highly fractionated view of organizational learning and knowledge management” (p. 572). Specifically, a team’s capacity to share, generate, evaluate and combine knowledge affects team learning (Argote 1999); the knowledge management and learning processes of teams are entwined. Further, although Nonaka (1994) argues that knowledge is

created by individuals, not teams or organizations, an emerging trend in the extant literature credits group outcomes not as a sum of individual achievements, but rather as the result of multi-level interactions between individuals and groups (e.g., Wageman 1995; Drazin et al. 1999; Hargadon & Bechky 2006).

Such thinking is consistent with the complex systems literature in which macro-level outcomes (often labeled as emergent behaviors) are credited as resulting from the outputs *and* interactions of system components, rather than just the summed outputs of the system components. Drawing heavily on Weick's (1995) sensemaking framework, creativity within groups, for example, is coming to be viewed as a interactive process rather than an outcome (see e.g., Drazin et al. 1999), and creative solutions are viewed as resulting not only from individual insights, but also the interactions of individuals in momentary collective processes such as help giving or reflective reframing (Hargadon & Bechky 2006). Current theorizing thus suggests that individual performance not only contributes to group processes, but is also influenced by group processes. Moreover, Barrett (1998) describes how uncertain task environments with equivocal information require "maxim[al] learning and innovation" (p. 605) and concurrently suggests that "management of knowledge development and knowledge creation" is a key responsibility for contemporary managers. Particularly in uncertain task environments, then, knowledge sharing—and perhaps more generically, knowledge management—emerges as an important group process for explaining individual and collective performance (Romme 1996; Barrett 1998; Fong et al. 2007; Edmondson et al. forthcoming). Testing these relationships empirically leads to the following hypotheses:

- *Hypothesis 5:* In a complex and interdependent task environment, knowledge sharing improves team learning
 - *Hypothesis 5a:* Similarly, when assigned complex and interdependent tasks, individuals operating in teams that regularly share knowledge will learn more quickly than individuals operating in teams that do not share knowledge

Nonaka (1994) argues that individuals, not organizations, create knowledge, and as a result "organizational knowledge creation ... should be understood in terms of a

process that ‘organizationally’ amplifies the knowledge created by individuals, and crystallizes it as part of the knowledge network of the organization” (p. 17). Given that organizations vary considerably on multiple dimensions, it is reasonable to extend Nonaka’s (1994) argument into an assertion that some organizations will prove more adept at “amplifying” the knowledge created by their members than others. As organizations depend upon information flows to carry individually-created knowledge from one organizational agent to a second and the structure of information flows within organizations can vary widely, we would expect that organizations with more optimal information flows relative to the task environment are able to leverage knowledge creation of its members more ably than other organizations undertaking similar tasks. Put differently and consistent with the longevity of structural and configurational concepts within organizational theorizing, then, we would expect that organizations that structure information flows in certain ways—as minimal as those structures may be (Barrett 1998)—will prove better poised to convert its members’ knowledge creation into higher performance than similar organizations with alternatively structured information flows. Although limited, this assertion is not without existing empirical support. Brooks’ (1994) work suggests, for example, that hierarchal structures constrain team knowledge sharing and hence result in suboptimal performance. This leads to a recapitulation of prior hypotheses:

- *Hypothesis 4:* In a complex and interdependent task environment, knowledge sharing improves team performance
 - *Hypothesis 4a:* Similarly, when assigned complex and interdependent tasks, individuals operating in teams that regularly share knowledge will outperform individuals operating in teams that do not share knowledge

F. WHY TEAMS?

Limited forays by Hollenbeck et al (2002) and others notwithstanding, structural contingency theory has generally been considered as useful at the organizational level of analysis, introducing questions about its efficacy at the level of work groups, or teams. A

Careful reading of empirical studies grounded contingent-theoretic concepts, however, suggests that the framework has often been deployed to explain work group variance with consistently promising results (see e.g., Baumler 1971; Reeves & Turner 1972; Argote 1982) even if organizational-level contingency theorizing has not proven entirely coherent (Schoonhoven 1981; Pearce & David 1983; Miner 2002). Pearce and David (1983) attribute these difficulties with organizational-level contingency theorizing with a failure to account for the impact of organizational design on work group structures, particularly the structure of work group information flows. Their comments suggest that perhaps work groups, not organizations, will continue to prove a more fruitful level of analysis for contingency-based theorizing. For the purpose of this dissertation, work team is defined as a “group of individuals who work *interdependently* to solve problems or carry out work.” (Kirkman & Rosen 1999, p. 58, emphasis added; see also Hackman 1987; Manz & Sims 1993) The terms teams and work team are used interchangeably with the term *work group* throughout the document.⁶

Pearce and David’s (1983) insights seem particularly apropos given growing emphasis on relationship of knowledge sharing on organizational and work group performance (Nonaka & Takeuchi 1995). In an investigation of performance among biotechnology firms, for example, Decarolis and Deeds (1999), find that knowledge flows—as evidenced by geographic location and alliances with similar firms and institutions—serve as a contributing factor for new product generation. Gupta and Govindarajan (2000) identify that certain characteristics of knowledge flows—such as “informality, openness and density of communications” (p. 475)—among subsidiaries of multi-national corporations contribute to the subsidiaries’ abilities to “transfer and exploit knowledge more effectively and efficiently” (p. 473). Focusing on the distribution of knowledge in teams, Rulke and Galaskiewicz (2000) similarly find that centralized or decentralized information flows mitigate a team’s ability to build competitive advantage given varying initial distributions of knowledge (i.e., clumped vs. dispersed) among the team members. These findings lead Anand et al (2003) to argue that attention to

⁶ Kerr and Tindale (2004) describe the distinction between research on team and small group performance as “fuzzy,” characterizing the distinction as “a rather artificial one that reflects more about subdisciplinary territoriality than about fundamental differences in focus or objectives.” (p. 624)

information management and information technology is inadequate for explaining the impact of knowledge sharing within teams, and that future teams-based knowledge research must address task complexity as a contingent factor.

While this prior work hints of contingent-theoretic models, only Birkinshaw et al (2002), Becerra-Fernandez and Sabherwal (2001), and Hutzschenreuter and Listner (2007) explicitly leverage contingency frameworks in their theoretical designs for knowledge transfer, and none of this prior work seems to adequately integrate structural contingency, information processing and knowledge flows theory at the work group level such that the hypotheses outlined in this chapter can be cogently tested. The research design outlined in the next chapter assists to address this gap in the literature through explicitly testing the hypotheses motivated in the prior sections.

G. SUMMARY

Dalton et al (1980) describe “the literature on structure-performance relationships ... [as] among the most vexing and ambiguous in the field of management and organizational behavior” (p. 60) and argue that “...the relationships between structure and performance remain empirical questions worthy of concentrated investigation” (p. 61). Continued scholarship in this vein (e.g., Hollenbeck et al. 2002; Beersma et al. 2003; Hoegl & Gemuenden 2001; Cummings 2004; Balkundi & Harrison 2006) implies that exploring the relationship of structure and performance continues to be highly generative (Gergen 1978). Schoonhoven (1981) adds that contingency theory has merit for explaining the relationship between structure and performance, but only when specified adequately and not overburdened with so many contingency variables such that conclusions are at best tenable. Findings from a growing number of scholars support the notion that organizational or population ecology-level contingency theorizing is less useful than contingency theorizing applied at the work group (i.e., team) level (see e.g., Reeves & Turner 1972; Argote 1982; Levitt et al. 1994; Wong & Burton 2000; Hollenbeck et al. 2002; Kim & Burton 2002; Beersma et al. 2003; Ilgen et al. 2005). Helpfully, however, concepts of structure developed within organizational theorizing—such as formalization, centralization and differentiation (see Hage & Aiken 1967; Hage et

al. 1971; Reimann 1973; Reimann 1974)—apply equally as well to work groups as organizations, allowing us to explicitly consider how structural contingency theory might contribute to explaining collective performance at the team level.

Moreover, well-understood dimensions of structure have been usefully translated into information-processing views of organizing (e.g., Levitt et al. 1994; Jin & Levitt 1996), allowing us to ground contingency-based theorizing using concepts of information and knowledge structures rather than power and authority structures. Concomitantly, the importance of knowledge sharing within teams, often built upon the information processing view of organizations, is becoming increasingly clear as an important consideration when explaining team performance (Nonaka & Takeuchi 1995; Decarolis & Deeds 1999; Gupta & Govindarajan 2000; Rulke & Galaskiewicz 2000; Becerra-Fernandez & Sabherwal 2001). Contingency theory has been posited as a useful framework for exploring the importance of knowledge sharing for collective performance (Birkinshaw et al. 2002; Hutzschenreuter & Listner 2007), but empirical findings from prior work suggest that an amendment of the underlying theoretical model from one of classic contingency theorizing (contingency predicts structure predicts performance) to more contemporary theorizing (contingency and structure interact to predict performance) is needed.

To integrate the three theoretical traditions of structural contingency, information processing, and knowledge flows theory, apply these research streams to explain team performance, and adequately respond to previous empirical findings, I created a theoretical model empirical testing. Consistent with the model and its instantiation of the theoretical intersection, I posited nine hypotheses for empirical investigation. For ease of the reader, I reiterate the hypotheses here prior to describing the research design in the next chapter:

- *Hypothesis 1:* In complex and interdependent task environments, Edge teams will outperform Hierarchy teams

- *Hypothesis 1a*: Similarly, when assigned complex and interdependent tasks, individuals working within Edge teams will outperform individuals operating within Hierarchy teams
- *Hypothesis 2*: In complex and interdependent task environments, transforming from an Edge to Hierarchy structure, and vice versa, will influence team performance
- *Hypothesis 3*: In complex and interdependent task environments, Edge teams will learn more quickly than Hierarchy teams
 - *Hypothesis 3a*: Similarly, when assigned complex and interdependent tasks, individuals working within Edge teams will learn more quickly than individuals operating within Hierarchy teams
- *Hypothesis 4*: In a complex and interdependent task environment, knowledge sharing improves team performance
 - *Hypothesis 4a*: Similarly, when assigned complex and interdependent tasks, individuals operating in teams that regularly share knowledge will outperform individuals operating in teams that do not share knowledge
- *Hypothesis 5*: In a complex and interdependent task environment, knowledge sharing improves team learning
 - *Hypothesis 5a*: Similarly, when assigned complex and interdependent tasks, individuals operating in teams that regularly share knowledge will learn more quickly than individuals operating in teams that do not share

III. RESEARCH DESIGN

In the literature review, I summarized and synthesized three distinct theoretical traditions—structural contingency, information processing and knowledge flows theory. Drawing from the work of others, I defined dimensions of structure—e.g., centralization, formalization and differentiation—within an information processing view of organizing. Embedding my theoretical model inside the structural contingency paradigm, I suggested that the interaction of information processing structures and knowledge sharing as a contingency variable could prove a fruitful approach for explaining collective performance. I identified and motivated several hypotheses related to this theoretical model.

In this section, I summarize the research design that guides a series of laboratory experiments to explicitly test the hypotheses motivated in the literature review. Building directly upon the work accomplished by Parity (2006), I first describe the ELICIT experimental environment, relating the experimental game to the complex, interdependent task environment that provided the context for the theoretical synthesis outlined in the prior section. I describe generally how the experimental environment relates to the theoretical model of information processing structures and knowledge sharing outlined previously (Figure 4). I then expand upon the subjects, protocols, controls, manipulations and measurements used for experimentation, relating them to the theoretically-motivated hypotheses outlined in Chapter 2. I close by discussing the rationale for exploring these hypotheses in a laboratory setting. Portions of the text are adapted from previous work (Leweling & Nissen 2007b).

A. EXPERIMENTAL ENVIRONMENT

ELICIT creates an experimental environment in which multiple players can undertake a complex, interdependent intelligence task. The environment allows researchers to manipulate the information processing structures to which subjects are assigned, and I extend the environment to allow for manipulation of knowledge sharing among the subjects. The environment also provides a well instrumented setting for

recording details about the micro-level information handling behaviors of each subject. ELICIT requires a team of subjects performing the roles of intelligence analysts to collaborate—in a network-centric, information-processing environment—and identify a fictitious and stylized terrorist plot. Central to identifying the fictitious terrorist plot is a set of 68 informational clues called “factoids.” Each factoid describes some aspect of the plot, but none is sufficient to answer all of the pertinent questions (i.e., who, what, where, when). The factoids are distributed among the 17 players in a series of steps: each player receives two clues initially, followed by one after five minutes of play and another after ten minutes have elapsed. The factoid distribution is designed so that no single player can solve the problem individually, and so that the team of players cannot solve the problem until after the final distribution. In other words, the players must collaborate to solve the problem, and they are required to do so for a minimum of ten minutes. Evidence from previous experiments (e.g., Parity 2006) suggests that play requires substantially more time (e.g., an hour or more). The game is thus characteristic of the complex and interdependent work commonly undertaken by knowledge workers (Janz et al. 1997; Schultze 2000).

Subjects play the game via client applications on separate, networked computer workstations. Each subject has access to a set of five functions supported by the client: 1) List, 2) Post, 3) Pull, 4) Share, and 5) Identify. The List screen displays all factoids that a particular player has received. For instance, after the initial distribution, a player’s List screen would display the two factoids distributed by the server. Post enables a player to have one or more factoids displayed on a common screen that can be viewed by other players. This represents one of two mechanisms for sharing information in the game (e.g., verbal and like communication is prohibited generally in most experiment protocols). Pull represents the complement to Post, as a player can display on his or her screen common information that has been posted. These post-pull functions are associated with four, separate screens, each corresponding to the pertinent questions (i.e., who, what, where, when) regarding the terrorist plot; that is, one screen includes information regarding who (e.g., which terrorist organization) might be involved, another includes information regarding what (e.g., which target might be attacked), and so forth

for information regarding where and when the attack might occur. Share represents the second mechanism for sharing information in the game, and enables players to send factoids directly to one another. Finally, Identify represents the manner in which subjects communicate their “solutions” to the problem, indicating via the software their conclusions regarding the pertinent questions (i.e., who, what, where, when) regarding the terrorist plot. All functions are logged by the server computer, and time-stamped to the nearest second.

Information processing function	Short description
List	Displays received factoids
Post	Places factoid on 'website' for access by other players
Pull	Displays website
Share	Sends factoid to another player – one factoid at a time
Identify	Communications solution

Table 6. Information Processing Functions Logged within Experimental Environment – Individual Level

Multiple versions of the game have been created, each of which is structurally similar but linguistically distinct. For instance, each version includes up to 17 players (and pseudonyms) and a set of 68 factoids. However, the factoids—and hence details of the terrorist plot—are unique to each version. Hence the potential exists to play the game multiple times, even with the same group of subjects. Additional, logically equivalent versions of the game can be created as needed. At the present time, four different versions have been created and shared. Each version includes two linguistically distinct but structurally equivalent sets of factoids with which experimentation can be undertaken.

After the game has completed, the moderator shuts down the server application, and researchers begin to analyze the transaction data captured by the server in text-file logs. Such data include time stamped entries for nearly every activity in the networked ELICIT environment, including, for instance, when and which factoids are distributed to each player, when and which factoids are posted to which common screens, when and which common screens are viewed by each player, when and which factoids are shared between each player, and the time stamped results of each player’s Identify attempt. The

game requires considerable cognitive and collaborative effort to play well (i.e., identify the pertinent details of a terrorist plot), but such effort is within the capabilities of many people and groups.

B. SUBJECTS

Subjects in this experiment represent a combination of (mostly) masters and PhD students and (a few) faculty members at the Naval Postgraduate School. Subjects are grouped into four sections: Group A is comprised principally of PhD students and some faculty in information science; Group B is comprised principally of masters students enrolled in an advanced command and control course; Group C is comprised principally of masters students enrolled in an introductory command and control course; and Group D is comprised principally of masters students with a special operations and/or intelligence background.

All subjects have undergraduate college degrees, and all possess or are working toward graduate degrees. Hence the subjects are representative in part of the kinds of relatively experienced and well-educated people who serve as professional intelligence analysts, particularly in national intelligence agencies. Further, all of the subjects have direct military or government service, and some have worked professionally in military or government intelligence organizations. The subjects are thus also representative of military and government employees who serve as professional intelligence analysts (Garst & Gross 1997). This sample serves to enhance the external validity of the study. External validity is bolstered by consistency with Hutchins et al's (2006) cognitive task analysis of intelligence work, which characterizes intelligence work as "an extremely challenging problem ...[in which] complex judgments and reasoning [are] required ... [and] high levels of uncertainty are associated with the data" (p. 282). Hutchins et al (2006) further demonstrate that intelligence professionals are often tasked with assignments beyond their primary area of expertise, indicating that use of subjects who are familiar with, but not experienced at, counterterrorism intelligence functions does not threaten this study's validity.

None of the subjects works currently as a professional intelligence analyst, and none of the four groups of subjects has worked together previously in an intelligence capacity. In this regard, the laboratory introduces some artificiality into the experiment. Additionally, despite the considerable level of realism designed into the ELICIT game, the information-sharing and -processing task is limited intentionally, so that people can play the game within an hour or two, and the networked-computer, ELICIT-mediated task environment does not enable all of the same kinds of media-rich communication modalities (e.g., telephone, video teleconference, face-to-face interpersonal and group interaction) likely to be found in operational intelligence organizations in the field. These factors serve to limit the external validity of the study. Limitations such as these are inherent within laboratory experimentation (McGrath 1982; Scandura & Williams 2000; Nissen & Buettner 2004), and call for the use of other, complementary research methods (e.g., fieldwork, see Van de Ven & Poole 2002) to ensure that a myriad of research traditions inform and thus help to refine theorizing about work groups (Chatman & Flynn 2005), often via triangulation (McGrath 1982; Scandura & Williams 2000). This dissertation is thus informed by complementary work (see e.g., Looney & Nissen 2006; Orr & Nissen 2006; Gateau et al. 2007; MacKinnon et al. 2007) and serves to inform a campaign of experimentation focused on the relationship of information processing structures with observed performance.

C. PROTOCOLS

Subjects are pre-assigned to play specific roles (e.g., as identified via pseudonyms) in the game, and to the extent possible, each subject plays the same role in every experiment session. In this particular experiment, subjects are pre-assigned to roles based upon their level of work experience. This is similar to the manner in which professional analysts are assigned to specific roles in operational intelligence organizations in the field, and hence helps to ground this experiment through conformance to practice. This approach contrasts a bit with that of randomized assignment imposed in some related studies (cf. Parity 2006; Lospinoso & Moxley 2007), emphasizing my concern for realism over replication.

Subjects read about the experiment, and consent formally to participate. When all ELICIT clients have connected with the server, subjects sit down at the appropriate workstations, are informed verbally about the nature of the experiment, and are asked to read a set of instructions pertaining to both the experiment and the ELICIT environment. The instructions for subjects are included at Appendix B. Subjects are encouraged to ask questions throughout this process. When subjects have read the instructions, and have had their questions answered satisfactorily, they indicate via the ELICIT client that they are ready to begin.

In this particular experiment, each of the four subject groups participates separately (e.g., on a different day of the week), and each group participates in a total of four experiment sessions, each time playing a different version of the game (i.e., Versions 1 – 4). For Groups A, B, and C, each of the four experiment sessions is spaced roughly one week apart; for Group D, experiment sessions are conducted twice a week for two weeks. These intervals between play provide time for subjects to reflect upon the game, and to interact with one another outside of the laboratory (e.g., as collaborating professional intelligence analysts do). Given that the subjects have many responsibilities outside of the laboratory experiments, this provides time also for subjects to forget about specific aspects of each session (e.g., as multitasking professional intelligence analysts do). Hence some learning and forgetting outside of the laboratory environment takes place between experiment sessions (Bailey & McIntyre 1992; Dar-El et al. 1995; Dar-El 2000; Devadas Rao & Argote 2006; MacKinnon et al. 2007). The specific schedule of play is described below.

Subjects are instructed not to reveal their pseudonyms to one another during the game. Indeed, they are instructed not to talk or communicate with one another during the game via any mechanism outside of the two summarized above (i.e., post-pull, share). This restriction simulates the kind of globally distributed, network-centric environment in which much intelligence work takes place operationally today. Additionally, subjects are allowed to send handwritten “postcards” directly to one another at periodic intervals in two of the four groups. Postcards contain the same information associated with an Identify function (i.e., who, what, where and when details). This extension enriches the

communication media available to the subjects beyond the artificially limiting factoid distribution enabled by the ELICIT software. To preserve anonymity, subjects send such postcards via the Experiment Moderator, who shuffles and delivers them to their intended recipients. Hence the sender of a postcard knows only the pseudonym of the receiver, and vice versa.

In addition to enriching the communication media, such postcards also capture in part the individualized knowledge of subjects about the impending terrorist attack at various points of game play. Specifically, the postcards are reflective of the sender's knowledge, as they represent a synthesis of the sender's interpretation of available information (e.g., factoids), and the sender completed the *action of preparing the postcard* for exchange. Similarly, *receipt* of the postcard enables the receiver to take action. For example, receipt of a postcard provides all the information necessary for the receiver to accept the sender's interpretation of the terrorist attack and complete the task by *submitting his or her identification*. Thus, receipt of a postcard enables the receiver to take a specific action (i.e., complete the task). The postcard thus instantiates *actionable* information, i.e., knowledge (Nissen 2006), within the experimentation. The postcards also represent a richer communications exchange (Daft & Lengel 1984; Daft & Lengel 1986) than what is provided by the game's Share function. Moreover, the postcards provide a mechanism for the players to *exchange knowledge* in the sense that they reflect an *action taken by the sender* (i.e., preparing the postcard) and an *action that could be taken by the receiver* (i.e., completing the task).

While subjects may share factoids (which may not be changed or edited in any way) with any player at any point in the game, only one postcard is allowed at each interval, coinciding approximately with the 15-, 25-, 35-, 45- and 55-minute marks in the game. This individually-created knowledge, captured on the experimental postcards, is collected from each player, regardless of group, by the Experiment Moderator. However, as described in the manipulations section below, in only two of the four groups are the postcards delivered to their intended recipients. Further, in the Edge configuration, the postcard may be sent to any other participant; in the Hierarchy, the postcard may be sent

only to a subordinate, supervisor, or within-team peer (e.g., subjects assigned to the “who” team may send the postcard only to peer on the “who” team).

	Experimental Device	Frequency of communication	Manipulation by Subjects
Information	“Factoid”	Unrestricted – player may send any factoid to any other subject at any time during game play	None, other than selecting which factoid to “share”
Knowledge	“Postcard”	Restricted – player may send one postcard to only one other subject at pre-specified intervals	Handwritten identification of attack details (e.g., who, what, when, where) and if desired, associated level of certainty (e.g., high, moderate, low, none)

Table 7. Comparison of Information Exchange Mechanisms in Experimental Protocol

Subjects are given incentives to play the game well. Subjects are given incentives also for personal gain (e.g., a “point” is awarded for an individual person that identifies the plot correctly in the shortest period of time) as well as for group gain (e.g., a “point” is awarded for the team that identifies the plot correctly in the shortest period of time). This is intended to mimic the dual nature of incentives that exist in professional intelligence environments, where people must cooperate for the organization to perform well, but who also compete against one another for limited rewards such as wage increases, promotions, desirable job assignments, and like intrinsic and extrinsic factors. The incentive structure is thus somewhat analogous to the profit-sharing incentive system described by Groves (1973). Further, of the 44 team-individual reward strategies identified by Cacioppe (1999), the game incentive structure provided public recognition (R10), praise (R11), feedback (R12), team-building (R19) and team attention (R20). Cacioppe (1999) describes these reward and recognition strategies as falling between extrinsic and intrinsic rewards, and specifically ascribes their utility for the two phases of the team life cycle most critical to the experiment—establishing itself (stage 2) and performing the task (stage 3).

Each subject is instructed to use the Identify function only once during game play. This represents the manner in which *formal* conclusions about terrorist plots in practice are taken very seriously, and how they impact other organizations (e.g., an operational organization may declare a state of emergency in preparation for or response to a suspected terrorist plot). Hence each player in the game is expected to wait until he or she is relatively confident about the plot before sending an “official” notice. Alternatively, the use of postcards above allows subjects to exchange the same knowledge informally with select other players. This represents the manner in which *informal* hypotheses are discussed and compared frequently within operational intelligence organizations.

The game can end in either of two ways: 1) when all players make their identification, or 2) when the Moderator must end the game due to time constraints. Generally, subjects are not told the results of the game (e.g., plot details) until after all four versions of the game have been played. This represents in part the kind of equivocality inherent in intelligence work: analysts are rarely certain about any suspected plot with absolute certainty (Knorr 1964; Handel 1990; Kean et al. 2004), and many are required to work on multiple plots either simultaneously or sequentially (Berkowitz 2004; Dearstyne 2005). Again, I go to considerable lengths to enhance the realism of the game—and hence external validity of the results. Finally, multiple instruments are administered to the subjects, at various points in time during the series of experiments. None of these instruments is administered during game play. They are described in the measurements section below.

D. CONTROLS

As noted above, each subject is pre-assigned a specific role to play, and is intended to play this specific role through each version of the game. Each version of the game is structurally equivalent, and both the ELICIT software and physical laboratory environments are invariant across experiment sessions. Further, via the instruments administered to the subjects and enacted within the ELICIT environment, researchers have the ability to control for myriad factors (e.g., personality, information-sharing,

experience) *ex-post* to the experiment sessions (Scheffé 1959; Kerlinger & Lee 2000). In general, I strive to control every aspect of the environment and experiment that is not manipulated expressly as described below in order to create a coherent factorial design. To the extent possible, I also match teams for gender, military Service (if applicable), military rank (if applicable), and age prior to experimentation, achieving the greatest uniformity between Groups B and C, in order to minimize between-group variance not attributable to the hypotheses outlined in Chapter 2.

To replicate real-world organizations, more experienced personnel are given roles of greater perceived responsibility – i.e., team leader, sub-team leader – in the Hierarchy configuration, as operationalized in the pseudonyms and role assigned to each player in the ELICIT environment. This preference for assigning more experienced personnel is continued into the Edge configurations to provide consistency across all four groups and all 16 experimental sessions. In the case of an absent player in one of these five key positions in the Hierarchy configuration, an experienced subject is promoted to fill the vacancy in a style similar to real-world organizations. A sub-team leader, for example, would serve as the team leader in his or her absence; similarly, the most experienced team member would serve for the sub-team leader in his or her absence. Less experienced subjects and those with known absences during the experimental period are assigned to team member positions under both configurations in order to minimize the impact of missing or transitory players on the experimental design. If the group played with fewer than 17 subjects, the experiment moderator would ensure that the missing player's factoids (four in total) are available to the other players via the software.

On occasion, the same subject plays with two different experimental groups. To minimize the effect of this play, the factoid sets are manipulated such that they are homomorphic, but linguistically unique (e.g., Blue Group → Green Group), during each round of experimentation. Any errors or misspellings noted in the factoid sets are repeated in the substitutes to ensure one-to-one correspondence of all factoid sets used during a particular round of experimentation. Repeat subjects are assigned positions of lowest relative responsibility, as well as a new pseudonym (which ensures a different distribution of factoids) during play in order to minimize their influence on group level

results. Anecdotal evidence from subjects, collected *post hoc*, confirms that subjects felt each play of the game is unique. Other statistical controls related to autocorrelation issues are discussed in Appendix D. However, the hypotheses as motivated specifically identify learning as an important dependent variable; as such, experimentation with subjects performing similar tasks *over time* is an important element of the experimental design.

E. MANIPULATIONS

The manipulations center on the research hypotheses motivated and summarized above. To test the first hypothesis regarding comparative performance of Edge and Hierarchy forms for both team and individual performance, subjects are assigned to corresponding experimental environments. No specific manipulations are associated with Hypothesis 3 except to repeat the basic experimental protocol four times with each group, and thus considering performance over time as an indicant of learning. Hypothesis 2 is addressed by assigning two teams to either the Edge or Hierarchy configurations for four sessions each to establish baseline performance (Groups A and D). Group B is assigned to a Hierarchy configuration for two sessions, and then switches to Edge for two sessions. Group C provides the comparative case through assignment to the Edge configuration for two sessions and then switching to the Hierarchy configuration for two sessions.

The first three hypotheses are thus addressed by manipulating the information processing structures to which the players are assigned during the experimental sessions. Important characteristics of the task environment—chiefly, complexity and interdependence—are held constant throughout all experimental sessions. Operationalizations of the task environment (e.g., complexity, interdependence) and information processing structure (e.g., centralization, formalization and vertical differentiation) are illustrated in Table 8 below. The operationalizations are consistent with prior work on information processing structures of work groups (Levitt et al. 1994; Jin & Levitt 1996; Kunz et al. 1998; Gateau et al. 2007).

	Definition	Operationalization	Edge	Hierarchy
Task Interdependence	Level of required interaction among team members to complete task (Katz-Navon & Erez 2005)	Each subject receives insufficient factoids required to "solve" puzzle without collaboration <ul style="list-style-type: none"> ▪ Edge and Hierarchy: 4 of 68 factoids distributed to each member over 10 minutes; none are sufficient to solve scenario 	High	High
Task Complexity	Level of cognitive demand required to resolve task; involves several interrelated and conflicting elements (Frost & Mahoney 1976; Campbell 1988)	Task requires high cognition and attentiveness from participants to solve; each experimental session requires novel solution <ul style="list-style-type: none"> ▪ Edge and Hierarchy: Approximately 20 factoids must be combined to solve puzzle while responding to communications from others; 50% of factoids are of no or limited utility for solving problem 	High	High
Team Centralization	Authority required to share information across team (Daft 2001; Kunz et al. 1998; Malone 1987)	Access to websites for storing and retrieving information <ul style="list-style-type: none"> ▪ Edge: All have access to all four websites ▪ Hierarchy: All but top leader has access to only one website; top leader has access to all four websites Restrictions on knowledge sharing: <ul style="list-style-type: none"> ▪ Edge: Any player may send "postcard" to any other player ▪ Hierarchy: Player may send "postcard" only to superior, subordinate or peer 	Low	High

	Definition	Operationalization	Edge	Hierarchy
Team Formalization	Extent to which rules and procedures reinforce roles and vertical levels (Daft 2001; Walsh & Dewar 1987; Reimann 1973)	<p>Website access reinforces role assignments</p> <ul style="list-style-type: none"> ▪ Edge: No restriction to website access ▪ Hierarchy: Website access restricted according to role assignment <p>Leadership and success:</p> <ul style="list-style-type: none"> ▪ Edge: Any player may serve as emergent leader at any given time; emergent leader's solution is important for group to "win" against other groups ▪ Hierarchy: Team leader and sub-team leaders are clearly identified to all players at start of play; team leader's solution is critical for group to "win" against other groups 	Low	High
Team Vertical Differentiation	Number of supervisory levels within the team (Blau 1995; Lawrence & Dyer 1983)	<p>Assignment of team roles:</p> <ul style="list-style-type: none"> ▪ Edge: All are team members ▪ Hierarchy: 1 x team leader, 4 x sub-team leaders, 12 x team members <p>Vertical levels:</p> <ul style="list-style-type: none"> ▪ Edge: One ▪ Hierarchy: Three <p>Heterogeneity of function:</p> <ul style="list-style-type: none"> ▪ Edge: None ▪ Hierarchy: Assigned to "Who," "What," "Where," or "When" sub-teams 	Low	High

Table 8. Operationalization of Task Characteristics and Team Structure within Experimental Environment

Hypothesis 4 emphasizes the influence of knowledge sharing on team (and individual) performance over time. Similarly, Hypothesis 5 emphasizes the influence of knowledge sharing on learning, which can be operationalized as observed performance

over time – i.e., longitudinal performance. As described above, in two of the groups, the artifacts for capturing actionable information (i.e., knowledge) are delivered to their intended recipients (see Table 7), while in the two experimental groups, this knowledge sharing is withheld. This sharing (or withholding) of individual assessments about the impending terrorist attack thus serves as the primary manipulation for addressing the influence of knowledge sharing on performance as outlined in Hypothesis 4 and Hypothesis 5. Combined, these two manipulations create a 2 x 2 mixed design that is consistent with the contingency theoretic framework outlined in the theoretical model (see Figure 5).

		Knowledge Sharing	
		<i>Not supported</i>	<i>Supported</i>
Information processing structure	<i>Hierarchy</i>	<ul style="list-style-type: none"> ▪ 2 groups ▪ 2 sessions per group ▪ Up to 17 players per session 	<ul style="list-style-type: none"> ▪ 1 group ▪ 4 sessions per group ▪ Up to 17 players per session
	<i>Edge</i>	<ul style="list-style-type: none"> ▪ 2 groups ▪ 2 sessions per group ▪ Up to 17 players per session 	<ul style="list-style-type: none"> ▪ 1 group ▪ 4 sessions per group ▪ Up to 17 players per session

Table 9. 2x2 Mixed Design

1. Hierarchy

In the Hierarchy organization manipulation, subjects are assigned to play roles within a three-level, functional, hierarchical organization as depicted in Figure 6. An overall leader (i.e., labeled “1”) is responsible for the intelligence organization as a whole, and has four functional leaders (i.e., labeled “2,” “6,” “10,” “14”) reporting directly. Each such leader in turn has three analysts (e.g., labeled “3,” “4,” “5”) reporting directly, and is responsible for one set of details associated with the terrorist plot. For instance, Subleader 2 and team would be responsible for the “who” details (e.g., which terrorist organization is involved) of the plot, Subleader 6 and team would be responsible for the “what” details (e.g., what the likely target is), and so forth for “when” and “where.” Subjects are shown this organization chart, told of their responsibilities within the organization, and provided with a short description of the hierarchy.

Additionally, the ELICIT software limits subjects' Post and Pull access to specific common screens within this manipulation. Specifically, those players in the “who” group, for instance, are allowed to Post to and Pull from only one of the four common screens (i.e., the “who” screen) noted above. Comparable restrictions apply to players in the other three functional groups. The only exception applies to the Leader 1, who has post-pull access to all four common screens. Further, I limit postcards to immediate superiors and subordinates within the organization. These manipulations reinforce the functional and hierarchical nature of the Hierarchy organizational form represented.

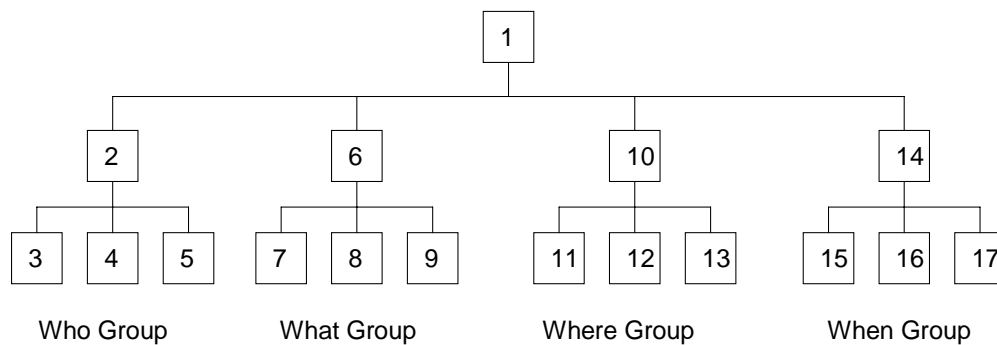


Figure 6. Hierarchy Organization (Leweling & Nissen 2007b)

Alternatively, players are allowed to use the Share function to send factoids to any of the 16 other players in the entire organization. This serves to capture the “flattening” effect of e-mail and similar, now-ubiquitous communication modes that enable peer-to-peer collaboration across formal organizational boundaries. Notably, however, the Share function is limited to sharing factoids only: no free-form or other information can be exchanged in this direct manner.

In the Hierarchy manipulation, the game ends when all the players identify the plot details, or when the game times out. However, the incentive structure ensures such that players *other* than the team leader receive individual recognition *if and only if* his or her pre-selected team leader identifies the plot correctly and in less time than the other two teams. This represents the manner in which leaders of many hierarchical organizations speak for the organization as a whole, and it captures the important information-sharing task of ensuring that such leader is informed well.

2. Edge

In the Edge organization manipulation, there are no pre-assigned leaders or functional groups established in advance of the experiment. Rather, consistent with current Edge conceptualizations, the group is leaderless and without form—what Mintzberg (1980) terms *Adhocracy*. As noted above, the players are pre-assigned to specific roles (i.e., pseudonyms) within the game, but the various roles reflect no hierarchical or functional differences from one another. As with the Hierarchy manipulation above, subjects are told about this organizational arrangement, and are provided with a short description of the Edge as an organizational form. I reflect the nature of this Edge manipulation in Figure 7, and note that the depiction resembles the concepts of an all-channel (Mackenzie 1966; Arquilla & Ronfeldt 2001) and mesh (Bordetsky et al. 2001; Bordetsky & Bourakov 2006) networks.

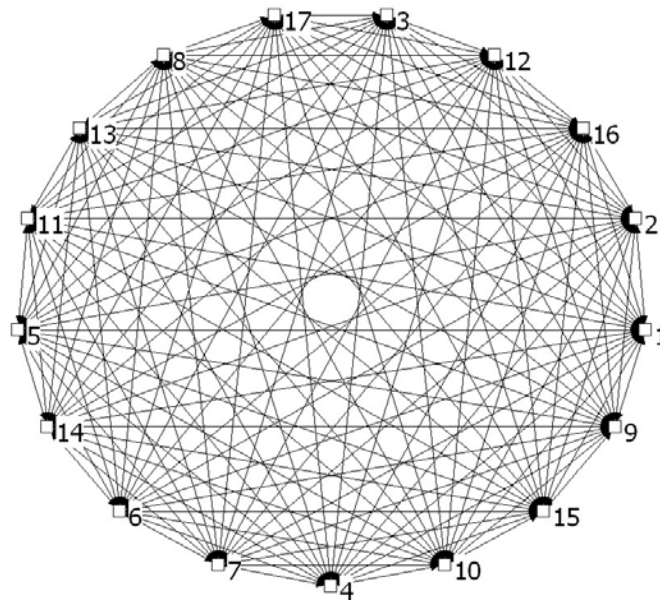


Figure 7. Edge Organization (adapted from Leweling & Nissen 2007b)⁷

⁷ Figure created using UCINET5 (Borgatti et al. 1999).

Without an overall leader or functional groups, subjects must decide for themselves who works on which aspects of the problem, and who posts, pulls and exchanges information with whom. With this manipulation, the ELICIT software does not limit subjects' Post and Pull access to specific common screens; that is, in contrast to the hierarchy manipulation above, any player can post to and pull from any of the four common screens (i.e., "who," "what," "when," "where"). In further contrast, any player can send a postcard to any other player, albeit within the same format, frequency and number constraints established for the hierarchy manipulation. Consistent with the other manipulation is the Share function, through which any player can share factoids directly with any other.

In the Edge manipulation, the game ends when all players Identify the plot details, or when the game times out. This represents the manner in which flat, leaderless organizations require some consensual decision making, and it captures the important information-sharing task of ensuring that all participants are informed well. To ensure comparability with the Hierarchy results, however, after the game has completed, participants are asked to elect *an emergent leader*, and this subject's game performance (e.g., evidenced via the Identify function) can be used for comparison with that of the team leader (i.e., Leader 1) in the Hierarchy manipulation.

3. Manipulation Sequence

Each of the four subject groups is assigned to a unique manipulation sequence as summarized in Table 10, and each group plays all four versions of the game once (i.e., each group plays a total of four times).

a. Structure

Group A plays according to the Edge manipulation all four rounds. Because we know relatively little about Edge organizations—particularly how they form and learn over time—this manipulation provides longitudinal data for exploration. Group D plays according to the Hierarchy manipulation all four times, offering a contrast to Group A. Groups B and C play twice each in the Hierarchy and Edge manipulations, but

the order of play is reversed. This sequencing reduces potential confounding from learning effects associated with order of play while also allowing exploration of the impact of structural transformation on performance (i.e., *Hypothesis 2*). These groups also play twice within each manipulation (e.g., twice in Hierarchy, then twice in Edge) before reversing. This sequence allows two experimental sessions for learning to occur within a particular team archetype.

The contrast between Group B and Group C reveals between-group effects of structural transformation on team performance. The contrast between Hierarchy and Edge manipulations reveals between-group effects for information processing structure for individual and team performance. The contrast between Hierarchy and Edge *over time* reveals between-group effects for individual and team learning.

b. Contingency

The second manipulation involves allowing or disallowing each subject to share his or her created knowledge about the impending terrorist attack via a highly structured data collection mechanism and timing criterion—operationalized as the sharing or withholding of “postcards” as outlined above. Briefly, in teams that are not supported by knowledge sharing (i.e., “nK”), each subject is required to complete postcards at specified intervals. However, the moderator collects these experimental devices and task no further action. In teams that *are* supported by knowledge sharing (i.e., “K”), each subject is not only required to complete the postcards at specified intervals, but also identify another player (whose identity is protected by pseudonym) to whom the postcard is to be delivered according to the protocol associated with the Edge or Hierarchy structure. The moderator maintains the identity of the pseudonym by collecting all postcards prior to delivering the postcards to the specified recipients.

Groups A and D play ELICIT while *not* supported by knowledge sharing during all experimental sessions, while Groups B and C play ELICIT while supported by knowledge sharing during all experimental sessions. The contrast between knowledge sharing supported and knowledge sharing not supported reveals between-group effects of

knowledge sharing on individual and team performance. Further, this same contrast *over time* reveals between-group effects of knowledge sharing on individual and team learning.

c. *Sequencing during Experimentation*

In Table 10, the experimental groups assigned to the Edge information processing structure are highlighted in **bold**, while the experimental groups assigned to the Hierarchy information processing structure are highlighted in *italics*. The *structural transformation* undertaken by Groups B (i.e., H-K to E-K) and C (i.e., E-K to H-K) is highlighted in the center of the manipulation sequence (yellow/light grey). The *recovery* of these two groups can also be compared (highlighted in blue/dark grey). Within the experimentation, the individual player represents the primary unit of analysis, but both individual and team levels of analysis are considered for assessing performance and learning.

Group	Session 1 V4	Session 2 V3	Session 3 V2	Session 4 V1
A – PhD	E – nK	E – nK	E – nK	E – nK
B – Advanced C2	<i>H – K</i>	<i>H – K</i>	E – K	E – K
C – Introductory C2	E – K	E – K	<i>H – K</i>	<i>H – K</i>
D – SOF / Intel	<i>H – nK</i>	<i>H – nK</i>	<i>H – nK</i>	<i>H – nK</i>

Key:

V1-V4: Elicit Version 1-4

H: Hierarchy manipulation

K: Knowledge sharing supported

E: Edge manipulation

nK: Knowledge sharing *not* supported

Table 10. Manipulation Sequence (adapted from Leweling & Nissen 2007b)

4. Relationship of Manipulation Sequence to Motivated Hypotheses

In this section, I discuss the relationship of the manipulation sequence depicted in Table 10 above with the motivated hypotheses.

a. Mitigation of Uncontrolled Learning Effects

As illustrated in Table 10, the manipulation sequence provides a well-structured and counterbalanced research design that equally weights the two independent variables of information processing structure (e.g., Edge, Hierarchy) and knowledge sharing (e.g., Supported, Not supported) for subsequent evaluation. For example, each combination of experimental conditions (e.g., Edge supported by knowledge sharing, Edge not supported by knowledge sharing, Hierarchy supported by knowledge sharing, Hierarchy not supported by knowledge sharing) is represented during each *round* of experimentation. This counterbalancing assists with mitigating between-group variance in the learning effects (Bradley 1958). Additionally, each experimental group plays each version of ELICIT one time, and moreover, each group plays each version of the game in the same order. This careful construction of game play for each experimental group further attenuates the influence of *uncontrolled* learning effects within the experimentation by mitigating errors introduced from variance between ELICIT versions.

b. Cross-sectional Comparisons

Since each group is assigned to a unique structure-contingency combination (i.e., E-K, E-nK, H-K, H-nK) during each round of experimentation and each group plays each version of ELICIT (i.e., Versions 1, 2, 3 and 4) in a pre-specified order, the manipulation sequence easily supports cross-sectional analysis. For example, the manipulation sequence provides four experimental sessions in which subjects complete the complex, reciprocally interdependent task under the E-K condition, four experimental sessions in which subjects complete the task under the E-nK condition, four experimental sessions in which subjects complete the task under the H-K condition, and so forth. Moreover, assigning at least one group to each structure-contingency combination *during each round of experimentation* allows for *post hoc* comparisons *within* and *between* each experimental round based on all four possible experimental conditions. For example, the Edge team supported by knowledge sharing (E-K) can be compared against all other groups during Version 1 play. Similarly, the Edge team supported by knowledge sharing (E-K) can be compared against all other teams during

Version 2 play. These results (i.e., the results from the Version 1 comparisons and the results from the Version 2 comparisons) can then be compared against each other. This careful design for the manipulations enables a rich set of cross-sectional comparisons, supporting Hypotheses 1, 1a, 4 and 4a..

c. Longitudinal Comparisons

Moreover, the experimental design allows for analysis of longitudinal data. Specifically, each group plays a version of ELICIT at approximately one week intervals, allowing for between-group and within-group comparisons *over time*. As each group is subjected to the *same* structure-contingency combination for at least two consecutive experimental sessions, within-group improvements in performance are easily compared (i.e., E-nK during Version 1 compared against E-nK during Version 2). Further, between-group improvements in performance are also easily compared (i.e., improvement of E-nK between Versions 1 and 2 compared against improvement of H-K between Versions 1 and 2). This meticulously planned manipulation sequence thus provides a rich set of comparisons using longitudinal data that scholars contend is critically important to contingency-theoretic research designs but not often available for analysis (Markus & Roby 1988; Delery & Doty 1996; cf. Keller 1994). Here the sequencing supports Hypotheses 3, 3a, 5 and 5a.

d. Structural Transformation

Finally, the manipulation sequence also provides for comparing the influence of structural transformation on team performance, as highlighted in the center section (yellow/light grey) of Table 10. With the start of experimental session three with groups B and C, the assignment of information processing structure is changed from the previous experimental session (i.e., Edge to Hierarchy, Hierarchy to Edge). This expressly planned switch allows one to compare the influence of a major structural transformation on two different groups transforming in two different directions while maintaining a counterbalanced design. Moreover, by waiting until the *third* experimental session to perform the transformation, the manipulation sequence retains the ability to

compare within-group and between-group *performance improvements*. By executing a fourth experimental session with each group, the manipulation sequence also allows observation of how teams *recover* from major structural transformations (in blue/dark grey). Here the sequence supports Hypothesis 2.

F. MEASUREMENTS

This section describes my operationalization schema for measuring performance and learning.

1. Performance

The first, second, and fourth hypotheses address comparative performance of teams and individuals as influenced by the two manipulations—information processing structure and knowledge sharing as a contingency variable. In this experiment, *performance* is operationalized as a two-dimensional dependent variable comprised of: 1) *time* to identify plot details correctly, and 2) *accuracy* of the plot identification. This measurement construct is informed by related computational experiments (see e.g., Nissen 2005a; Looney & Nissen 2006; Nissen & Sengupta 2006; Orr & Nissen 2006), in which *time* and *accuracy* (related to *risk*) reveal consistently insightful results. The measurement construct is also informed by literature in the psychological and organizational domains that suggest a trade-off exists between time and accuracy in tasks requiring high cognition and/or advanced motor skills (see e.g., Meyer et al. 1988; Rogers & Monsell 1995; Guzzo & Dickson 1996; Plamondon & Alimi 1997; Elliott et al. 2001; Beersma et al. 2003) at both the individual and team/group levels of analysis. These performance measures also provide an objective, consistent measure of team performance that is not dependent upon self-reported perceptions of subjects (Lenz 1981).

a. Time

In the first component, *time* pertains to when a subject submits his or her identification of the terrorist plot, with group performance with respect to time

operationalized as the mean submission time of all subjects participating during the experimental session. For ease of comparison, the scales for both measurements are linearly transformed on a scale ranging from 0 to 1, with 1 being more desirable in both cases (e.g., more quickly, more accurate). Measuring and linearly transforming time is straightforward, as the time for each subject's identification is logged to the nearest second by the software. To ensure that the measurements are meaningful when compared against values from all 16 experimental sessions, I determine that identifications made at the same 'clock' time during two different sessions (e.g., after 2200 seconds has elapsed since the start of Session 1 and after 2200 seconds has elapsed since the start of Session 2) are to be considered exactly equal. Each subject's identification time is thus calculated using Equation 1:

$$T = \frac{\text{max_time} - \text{identification_time}}{\text{max_time}} \quad \text{Eq. (1)}$$

In Equation 1, *max_time* represents the maximum time elapsed (in seconds) during all 16 experiments.

b. Accuracy

In the second component of performance, *accuracy* refers to when the subject has identified the specific details of an impending terrorist attack – i.e., who, what, where and when, with group performance for accuracy operationalized again as the mean accuracy of identifications provided by subjects during the experimental session. Sufficient information is contained within the factoid sets such that the subjects can discern the group responsible for the attack (“who”), the target of the attack (“what”), the country in which the attack will take place (“where”) and the month, date and time of the terrorist attack (“when”). For the results reported here, I operationalize accuracy according to strict criteria, with a subject receiving a high score on accuracy if his or her identification of the terrorist attack reduced decisionmaker uncertainty *exactly*. My model is thus consistent with Heuer's (1999; 2004) description of intelligence analysts as agents that filter and make sense of scattered and potentially incomplete information on behalf of policy makers, informing policy makers by reducing uncertainty about complex topics. A subject receives credit for his or her identification under this strict schema if it

matches the correct response exactly, with some reasonable exceptions for natural language equivalents and use of “military time” (i.e., 24-hour clock) by many respondents. A point is awarded for each component of the correct answer – group, target, country, month, date, and time of day – and then linearly transformed to a scale from 0 to 1, with equal weighting for the who, what, where, and when components. No points are awarded for blank (i.e., non-) answers. An illustration of the operationalization is provided at Appendix C.

2. Learning

The third and fifth hypotheses address the influence of information processing structures and knowledge sharing on learning. I operationalize *learning* as the change in performance over time and repetition, and use the same, two-dimensional dependent variables of *time* and *accuracy* summarized above. Specifically, I measure the change in performance across the four experiment sessions—blocking by organizational form and knowledge sharing.

G. WHY LABORATORY EXPERIMENTATION?

Laboratory experimentation has been employed to dampen the effects of extraneous variables when testing theoretical constructs, while illuminating the inferential relationships between variables of a cogent theoretical model (Shadish et al. 2002). Laboratory experimentation has proven especially useful within information science research (Jarvenpaa 1988). Designed well, laboratory experimentation can lead researchers to new, highly reliable knowledge obtained in settings that are straightforward to replicate (Kerlinger & Lee 2000). While challenged for not providing the external validity inherent within field studies, laboratory experimentation contributes to full cycle theorizing (Chatman & Flynn 2005) in which insights gleaned from field studies can be tested in a more controlled environmental setting. Confirming insights from field studies in a laboratory serves as an additional verification that theory is moving toward cogent explanation, while refuting insights gleaned from field studies offers opportunities to reconsider theoretical relationships.

Laboratory experimentation can also prove exploratory, particularly when constructs and their relationships are tested at the edges of theoretical boundaries. Extreme phenomena or settings are often the subject of case-based research (Yin 2003), but the paucity of instances of extreme phenomena (or inability to capture desired data related to such events) makes generalizing difficult. Laboratory experimentation offers opportunities to test theory at various boundary conditions—including extreme conditions—when carefully designed. By creating information processing structures of Edge and Hierarchy in the laboratory and subjecting these archetypal structures to contingency conditions in which knowledge sharing is permitted or disallowed, the research design outlined above offers an opportunity to explore how the boundaries of a carefully articulated parameter space relates to an observed performance space. Such studies can prove particularly useful if the transformation relationship between the parameter and performance space proves to be isomorphic (i.e., one-to-one), as illustrated the *nominal* transformation relationship illustrated in Figure 8 below. In the figure, I depict the two independent variables, knowledge sharing and information processing structure, in the parameter space along orthogonal axes. These axes thus represent the independent variables as well as the experimental manipulations used within the experimental environment. The transformation function, Φ , represents the assignment of a complex, interdependent task to the subjects within the experimental environment, and thus represents a function that links the independent and dependent variables. The performance space is characterized by the two dependent variables, time and accuracy, again placed on orthogonal axes. A correlation check and discriminant analysis is performed on the experimental data to verify that these dependent variables are, indeed, appropriately represented as being generally orthogonal.

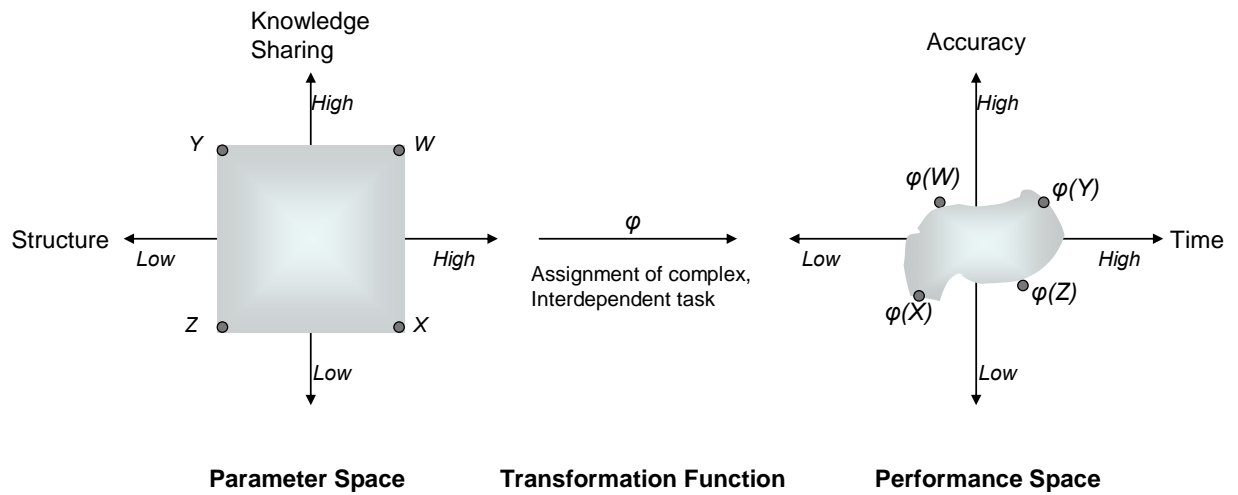


Figure 8. Nominal Transformation Relationship between Parameter Space and Performance Space

Given the newness of the Edge configurations to organizational design (Orr & Nissen 2006; Leweling & Nissen 2007b) and studies that demonstrate organizational structures in field research differ from pure archetypes (Doty et al. 1993), laboratory experimentation thus seems a natural candidate for exploring the influence of information processing structures and knowledge sharing on team performance, particularly along the boundary conditions of low/high centralization, low/high formalization and low/high vertical differentiation.

H. ANALYTICAL METHOD

As outlined in this chapter, the experimental design involves manipulating two dichotomous independent variables of information processing structure (i.e., Edge, Hierarchy) and knowledge sharing (i.e., supported, not supported). Moreover, the experimental design involves measuring two dependent, continuous performance variables (i.e., time and accuracy) during the experimentation. As the design and manipulation sequence ensure that the independent variables are not highly correlated, analysis of variance (ANOVA) is generally the most appropriate technique for analyzing

the data (Kerlinger & Lee 2000, pp. 484-485), particularly if the data meet assumptions of normality of distribution and homoskedasticity. Additional detail is provided in Chapter IV.

I. SUMMARY

Leveraging the ELICIT experimental environment, I operationalize the intersection of structural contingency theory, information processing, and knowledge flows theorizing within a multi-player intelligence game with high task complexity and task interdependence. Using a 2x2 mixed design, four teams of approximately 17 participants each are subjected to two manipulations. The first manipulation transforms the information processing structure to which the subjects are assigned, informed by recent work (Orr & Nissen 2006; Gateau et al. 2007) comparing Edge (i.e., low centralization, low differentiation, low formalization) and Hierarchy (i.e., high centralization, high differentiation, high formalization) configurations and built upon structural contingency theory. The second manipulation alters sharing of actionable information (i.e., knowledge), informed by theorizing (Nonaka 1994; Nonaka & Takeuchi 1995; Argote et al. 2003; Nissen 2006) and field work (Rulke & Galaskiewicz 2000; Birkinshaw et al. 2002; Haas 2006) in this domain. Consistent with laboratory experimentation (Jarvenpaa 1988; Shadish et al. 2002), controls on the information processing structures and knowledge sharing of the subjects are enacted to implement these manipulations in the experimental environment. To enhance the external validity of the design, the experimental protocol and task replicate a common intelligence analysis charge—identification of possible terrorist attacks—in a structured, repeatable manner. Demographic data on subjects are used to assign subjects to teams and roles according to experience, gender, and Service (if applicable) to minimize variance, bolster realism and thus enhance external validity. Measures of *team* and *accuracy* are developed to assess the objective performance at both the team and individual level of analysis. The combination of these subjects, manipulations, controls, and measures—all within a laboratory environment—serves to strengthen research design factors that enhance

internal and external validity of the study. Results and implications of the experimentation follow in subsequent chapters.

J. INSTITUTIONAL REVIEW BOARD

The research design described in this chapter involves experimentation with human subjects. Pursuant to university regulations (Naval Postgraduate School 2002) and principles of ethical research (American Psychological Association 2001; Shadish et al. 2002 pp. 279-291), Institutional Review Board approval has been obtained for the experimentation. A copy of both the submission and approval is available at Appendix A.

IV. DATA CODING AND INITIAL ANALYSIS

In Chapter II, I concluded with nine hypotheses motivated by a unique theoretical intersection – structural contingency theory, information processing theory and knowledge flows theory. In Chapter III, I outlined an experimental research design intended to explicitly address the motivated hypotheses. I also briefly discussed using analysis of variance as my primary analytical technique, consistent with research designs involving experimentation.

In this chapter, I summarize the results of the experimentation outlined in Chapter III for the hypotheses motivated in Chapter II at both the individual and team levels of analysis. I begin by discussing the observations collected during the experimentation, controls enacted to ensure a quality data set, and results of a check to ensure consistency of the observed results with the proposed research design. I then briefly review the coding schema for the independent and dependent variables important to the quantitative analysis presented during subsequent analysis. Specifically, I identify variables at the individual and team levels of analysis for both performance and learning. I highlight some essential characteristics of the observations associated with the dependent variables, concentrating on tests for normality, homoskedasticity, and homogeneity of covariance that are important for determining whether quantitative analyses of the experimental results are better suited to parametric or non-parametric methods for testing the hypotheses. I close by ensuring that detailed investigation of the results are warranted by reviewing multivariate results for individual performance, individual learning, team performance and team learning. More detailed analyses of the main and interaction effects follow in Chapter V and VI, respectively. Short portions of the text are adapted from previous work (Leweling & Nissen 2007b). Readers most interested in the results of initial analyses may wish to skip to the summary section located at the end of the chapter.

A. OBSERVATIONS

In this section, I briefly describe important characteristics about the data collected during the experimentation, consistency of the observations with the proposed research design, and handling of exceptions to planned observations in order to ensure quality control of the data.

1. Overview

The sixteen experimental sessions are conducted over a 36 day period. Groups occasionally play ELICIT with fewer than the desired 17 players, but the experimental protocol ensures that in all but one experimental session, subjects access all information needed to completely discern all details about the impending terrorist attack.⁸ A total of 69 unique subjects play the game from 1 to 8 times ($\mu = 3.51$, $\sigma = 1.71$), with over 97% of subjects submitting at least one identification during the experimentation. The subjects range in age from 22 to 62 ($\mu = 35.48$, $\sigma = 8.52$), with years of work experience ranging from 1 to 38 years ($\mu = 11.72$, $\sigma = 8.41$). Each ELICIT experimental session involves between 39 and 65 minutes of game time. The experiments yield 210 cases for evaluation for which the subjects' identification data of the terrorist attack are explicit and 234 cases for evaluation when the 24 non-answers are included for analysis.⁹ On occasion, the author and three committee members participate in the experimentation with Group A (PhD Group). However, the analysis presented here omits associated data.

2. Omission of Some Observations from Analysis

Although instructed to provide their assessment of the details of the impending terrorist attack only once (e.g., who, what, where and when), subjects occasionally submit their identification of the terrorist attack two or more times. For consistency in the analysis and with the instruction set to the players, however, all results reported here

⁸ The exceptional case represents the pilot experiment in which the subjects do not receive a factoid related to the exact hour of the impending attack. All other information, however, is available to the players during this session.

⁹ In such cases, time is set to zero, as is accuracy (i.e., worst possible performance).

reflect only the subject's *first* identification, regardless if a subsequent identification was more accurate. The results of these 210 cases are provided in Table 11 below. The observation set that includes 24 cases in which no identification was submitted is provided in parentheses.

		Information Processing Structure		
		<i>Edge</i>	<i>Hierarchy</i>	Total
Knowledge Sharing	<i>Supported</i>	66 (67)	62 (68)	128 (135)
	<i>Not supported</i>	46 (57)	36 (42)	82 (99)
	Total	112 (124)	98 (110)	210 (234)

Table 11. Cross-tabulation of Observations

3. Consistency of Observations with Proposed Design

Kerlinger and Lee (2000 p. 775) suggest that in multivariate research designs, correlation of independent variables should be checked to ensure consistency with the research design, simplify interpretation of results, and confirm sufficient data are available to infer both main and interaction effects. This inspection also assures that the experimentation as executed is consistent with the experimentation as proposed and assists with determining whether analysis of variance (ANOVA) and multivariate analysis of variance (MANOVA) methods are appropriate analytical tools for the subsequent analysis.

As the independent variables are nominal (e.g., Structure—Edge or Hierarchy, Knowledge Sharing—Supported or not Supported) and dichotomous, Kendall's tau (τ) method is used rather than Pearson's method to determine correlation of independent variables (Howell 1997; Field 2005). Kendall's tau correlation (Arndt et al. 1999) reveals that the two manipulations—1) information processing structure and 2) knowledge sharing—are not highly correlated.¹⁰ Given the manipulation sequence as described in Table 10, the Kendall's tau correlation coefficients for the independent variables are as

¹⁰ Spearman's rho correlation method is also appropriate and provides similar results.

expected (see Table 12) and confirm the robustness of the basic research design for providing useful data to test the stated hypotheses using analyses of variance and related statistical techniques.

		Information Processing Structure	Knowledge Sharing	ELICIT Version
Information Processing Structure	Correlation Coefficient	1.000 (1.000)	.044 (.079)	-.008 (-.004)
	Sig. (2-tailed)	.	.521 (.230)	.905 (.944)
Knowledge Sharing	Correlation Coefficient		1.000 (1.000)	.015 (.002)
	Sig. (2-tailed)		.	.815 (.980)
ELICIT Version	Correlation Coefficient			1.000 (1.000)
	Sig. (2-tailed)			.
	N	210 (234)	210 (234)	210 (234)

Table 12. Kendall's Tau Correlation Coefficients for Independent Variables

B. DATA CODING

The results reported in this chapter are created using SPSS statistical analysis software, release 15.0.0. Use of quantitative methods to test the hypotheses as motivated in the previous chapter requires coding and storing the data within a SPSS spreadsheet. In this section, I briefly review the variables as coded for analysis at the individual and team levels of analysis. I begin with outlining my coding schema for performance at the individual level of analysis, followed by learning at the same level of analysis. I then transition to a discussion of my coding schema for performance and learning at the team level of analysis. Time data are logged by the server computer to the nearest second throughout all 16 experimental sessions.

1. Individual Performance

In this section, I define the independent and dependent variables associated with performance at the individual level of analysis. Each of the 234 observations is coded for all variables, and the data are reviewed multiple times to correct any coding errors. These variables assist with analysis of *Hypotheses 1a* and *4a*, which predict that

individuals in Edge teams will outperform individuals within Hierarchy teams and individuals within teams supported by knowledge sharing will outperform individuals within teams not supported by knowledge sharing, respectively.

a. *Independent Variables*

A total of six independent variables are coded, all of which are nominal. The first variable, *Subject_ID*, represents a unique character string assigned to each of the 69 subjects participating in the experiment. The second variable, *Group*, represents the unique numeric code assigned to each of the four groups of the study as outlined in Table 10. The third and fourth variables represent direct operationalizations of structure and contingency as developed in the theoretical model (see Figure 5). Specifically, the third variable, *Structure*, represents the two information processing structures created by the manipulation of centralization, formalization and differentiation (i.e., 1 – Edge, 2 – Hierarchy) within the experimentation. The fourth variable, *Knowledge*, represents the knowledge sharing variable (i.e., 1 – not supported, 2 – supported) within the theoretical model and operationalized as “postcards” during the experimentation. The fifth variable, *Structure_Knowledge*, represents an amalgamation of the previous two variables, with the nominal values differentiated by the combination of both information processing structure and knowledge sharing to which the subject was exposed (i.e., 1 – Edge without knowledge sharing, 2 – Edge with knowledge sharing, 3 – Hierarchy without knowledge sharing, 4 – Hierarchy with knowledge sharing). The sixth variable, *ELICIT*, represents the variant of the ELICIT game played when the observation was taken and is coded numerically (e.g., 1 – ELICIT version 1, 2 – ELICIT version 2, and so forth). Only the two independent variables stemming from the manipulations of the experimental design, i.e., *Structure* and *Knowledge*, are used for subsequent analysis. Coding of all other variables assists with quality control during the data coding process.

b. *Dependent Variables*

Performance data are coded consistent with the measurement schema outlined in the previous chapter. The two performance measures of *Time* and *Accuracy*

are dimensionless scales. While *Time* is originally measured in seconds and *Accuracy* is originally measured in points, the data are subjected to linear transformation such that the value representing lowest performance on either factor is zero and the value representing highest performance on either factor is 1. For time, this linear transformation means that zero represents the *slowest possible response* during experimentation while one represents the *fastest possible response*. For accuracy, this linear transformation means that zero represents the *least accurate identification possible (i.e., completely incorrect response)* while one represents the *most accurate identification (i.e., completely correct response)*. These linear transformations are accomplished for both clarity and consistency. Non-responses (i.e., instances in which the subjects did not provide an explicit identification of the impending terrorist attack) are left blank. To support more detailed analysis, two dependent performance variables, also scalar, are later added: *Time_nonresponse_as_zero* and *Accuracy_nonresponse_as_zero*. These two variables are nearly identical to *Time* and *Accuracy* created previously, with the exception that non-responses are coded as zero for both, representing the lowest possible performance on both dimensionless scales.

2. Individual Learning

In this section, I briefly describe the independent and dependent variables introduced to the coding schema to test learning hypotheses at the individual level of analysis. These variables support testing *Hypotheses 3a* and *5a*, which predict that individuals within Edge teams will learn more quickly than individuals within Hierarchy teams and individuals supported by knowledge sharing will learn more quickly than individuals not supported by knowledge sharing, respectively.

a. Independent Variables

Most individuals play with the same experimental group (i.e., A, B, C, or D, see Table 10) throughout, but on occasion, some individuals are absent from a particular experimental session and thus 1) may play the game with an alternate experimental group, or 2) rejoin their group after its information processing structure has

been manipulated to an alternate form (e.g., experimental groups B and C). With the data as collected, then, one cannot assume that the learning observations at the individual level of analysis exactly follow the manipulation sequence outlined in Table 10. Additionally, experimental groups B and C switch information processing structures at the midpoint of the experimental series, and thus learning data attributed to operating within a particular information processing structure *over time* must be carefully coded for accuracy. As a result, I add three additional independent variables to ensure quality analysis.

Specifically, I create three nominal variables associated with learning: *Learn_Structure*, *Learn_Knowledge*, and *Learn_Structure_Knowledge*.

Learn_Structure represents the similarity or difference between the information processing structures to which the subject is assigned between any two *consecutive* observations of performance. For example, an observation associated with a subject assigned to an Edge information processing structure whose next subsequent play of the game also occurred within an Edge information processing structure is assigned the nominal value 1 for this variable. Similarly, an observation associated with a subject assigned to an Edge information processing structure whose next subsequent play of the game was when assigned to a Hierarchy information processing structure is assigned a nominal value 2 for this variable. The process continues for the other two possibilities (i.e., 3 – Hierarchy to Hierarchy, 4 – Hierarchy to Edge). Coding for the nominal variable *Learn_Knowledge* proceeds similarly, except that *Learn_Knowledge* distinguishes between knowledge sharing conditions (i.e., 1 – knowledge sharing not supported remaining knowledge sharing not supported, 2 – knowledge sharing not supported changing to knowledge sharing supported, 3 – knowledge sharing supported remaining knowledge sharing supported, 4 – knowledge sharing supported changing to knowledge sharing not supported).

Learn_Structure_Knowledge represents a selected amalgamation of the previous two variables given the hypotheses motivated in the previous section (i.e., *Hypothesis 3*, *Hypothesis 3a*, *Hypothesis 5*, and *Hypothesis 5a*). Specifically, the nominal categories within the variable *Learn_Structure_Knowledge* code observations associated with consecutively consistent conditions – e.g., a player is consecutively

subjected to the Edge information processing structure without knowledge sharing or the player is consecutively subjected to the Hierarchy information processing structure with knowledge sharing. All observations not within this scope are ignored (i.e., left blank in the SPSS worksheet) since they fall outside of the motivated hypotheses. These leads to four coding possibilities for the *Learn_Structure_Knowledge* variable (i.e., 1 – consecutive play of Edge information processing structure without knowledge sharing, 2 – consecutive play of Edge information processing structure with knowledge sharing, 3 – consecutive play of Hierarchy information processing structure without knowledge sharing, and 4 – consecutive play of Hierarchy information processing structure with knowledge sharing).

b. Dependent Variables

Two dependent variables, both scalar and dimensionless due to the prior linear transformation applied to the performance data, are added to support analysis of information processing structure and knowledge sharing on learning at the individual level of analysis, *Learn_Time* and *Learn_Accuracy*. *Learn_Time* represents the difference in performance in the variable *Time* between a subject's two consecutive plays of the game. Similarly *Learn_Accuracy* represents the difference in performance in the variable *Accuracy* between a subject's two consecutive plays of the game. The dimensions of these variables thus represent change in performance from one experimental session to the next subsequent experimental session. This measure represents a variation of classic learning curve studies (e.g., Asher 1956) in which learning is represented as change in performance (in Asher's case, improved performance equated to lower per unit production cost) as a task is repeated over time.

3. Team Performance

In these next two sections, I describe variables created to code data at the team level of analysis. I begin with discussing the aggregation technique used to create the data at the team level of analysis, and I then discuss the specific variables associated with performance and learning at this collective level. These variables support testing

Hypotheses 1, 2 and 4. Hypothesis 1 predicts that Edge teams will outperform Hierarchy teams. *Hypothesis 2* predicts that transforming from Edge to Hierarchy, and vice versa, will influence team performance. *Hypothesis 4* predicts that teams supported with knowledge sharing will outperform teams not supported with knowledge sharing.

a. Measurement

Measurement of team performance remains a complex topic within the psychological and organizational literature. Differences in measuring team performance generally occur along three dimensions – 1) who (or what) serves as the observer and/or assessor of the team's performance, 2) the measuring instruments and devices used to collect the observations, and 3) the aggregation mechanisms associated with the observations (Hallam & Campbell 1997; Tesluk et al. 1997; Stewart & Barrick 2000; Politis 2003; Stewart 2006). Within the literature, team members or outside observers (or sometimes both) collect and report observations about team performance (Tesluk et al. 1997). In some studies, for example, team member perceptions of team performance are paramount (e.g., Murnighan & Conlon 1991), while in others, external observers report on team outcomes (e.g., McIntyre & Salas 1995). The measuring instruments used to elicit data about team performance vary from open-ended interview questions to carefully calibrated instruments (e.g., surveys, stop watches, see Tesluk et al. 1997). Appropriate methods of aggregating these observations have spawned a simmering debate within the psychological and organizational literatures (Klein & Kozlowski 2000; Fossey et al. 2002; English et al. 2004; Marks et al. 2005; Stewart et al. 2005; Stewart 2006), but two common methods include 1) aggregating observations about various team member outputs into a team level measure and 2) aggregating observations about a singular team output into a team level measure. This study uses the former approach. Specifically, the mean performance of subjects' individual performance, *including non-responses*, is calculated for each experimental group after each experimentation session. Those means become measures of team performance are then compared according to the manipulations of interest (e.g., Hollenbeck et al. 2002; Beersma et al. 2003).

Failure of individuals to perform while reaping benefits from team participation, sometimes characterized as the “free rider” effect (Olson 1965), social loafing (Latané et al. 1979; Kameda et al. 1992) or a non-contribution strategy (Golle et al. 2001),¹¹ is a long-standing phenomenon in the team literature (Harkins & Jackson 1985; Kidwell & Bennett 1993; Gagné & Zuckerman 1999; Hamilton et al. 2003). Such failures, Zárraga and Bonache argue (2003; 2005), can pose particular problems for team tasks involving knowledge creation and transfer. Given the importance of these constructs relative to team research generally and team performance specifically, I choose to include the 24 cases in which subjects do not provide an identification of the impending terrorist attack (i.e., fail to complete the assigned task) in the analyses of team performance and team learning.

The team performance measures are thus distinctive from the individual performance measures in two important ways. First, the team measures include the 24 observations in which the subjects fail to complete the task in the calculations. Specifically, cases in which subjects failed to complete the task (i.e., provided no identification of the impending terrorist attack during the experimentation) are coded as zero for both time and accuracy (i.e., lowest possible performance). Further, team performance reflects the mean individual performance by each team during each experimental session. Although exceptional care is taken during the experimentation to balance teams according to gender, Service, rank and number of participants, teams on occasion play with fewer than the desired 17 players. An experimental protocol ensures that impact on the experimentation is minimal, and team measures are compared as adjusted for the number of subjects present during the experimentation. Mathematically, the difference involves creating the team performance measure by dividing the sum of subject scores for each dependent measure by the number of subjects present for experimentation. This approach ensures greater consistency for comparing team performance across experimental conditions and over time.

¹¹ Kidwell and Benett (1993) integrate these concepts into a singular “propensity to withhold effort” construct.

b. Independent Variables

Several of the independent variables useful for the individual level of analysis are also helpful at the team level of analysis. Specifically, each observation of a team's mean performance is coded by *Group* (represents the unique code assigned to each of the four groups of the study), *Structure* (represents the two information processing structures of 1 – Edge, 2 - Hierarchy), *Knowledge* (represents the knowledge sharing condition of 1 – not supported, 2 - supported), *Structure_Knowledge* (represents the quadrant of the basic research design) and *ELICIT* (represents the variant of the ELICIT game). All variables are nominal and coded using the same category labels (e.g., for *Structure*, Edge = 1 and Hierarchy = 2) as the individual level of analysis. Only the two variables associated with the manipulations—i.e., *Structure* and *Knowledge*—are used for subsequent analysis; the others are incorporated to reduce coding errors.

c. Dependent Variables

Like the independent variables, dependent variables for team performance parallel similar variables at the individual level of performance. Specifically, *Team_Time* represents the mean time of its constituent members during each experimental session and *Team_Accuracy* represents the mean accuracy of its constituent members during each experimental session.

d. Team Performance under Structural Transformation

Experimental Groups B and C switch information processing structures (i.e., Edge to Hierarchy, Hierarchy to Edge) between the second and third rounds of experimentation. To measure the influence of this structural transformation on team performance, I measure the differences of team performance for time and for accuracy between the third experimental session and the second, coding for variables *Team_Transformation_Time* and *Team_Transformation_Accuracy*, respectively. These scalar variables serve as my dependent measures. I also code a nominal independent variable, *Team_Transformation*, using the schema of 2 – Edge transforms to Hierarchy and 4 – Hierarchy transforms to Edge.

4. Team Learning

In this section, I describe the independent and dependent variables associated with the team learning. These variables support analyses of *Hypotheses 3* and *5*, which predict that Edge teams will learn more quickly than Hierarchy teams and teams supported with knowledge sharing will learn more quickly than teams not supported by knowledge sharing, respectively.

a. Independent Variables

For learning, the independent variables at the team level closely parallel the independent variables at the individual level of analysis. Specifically, I add the nominal variable *Team_Learn_Structure* to the data set to represent the team's information processing structure, coded as 1 – Edge remains Edge and 3 – Hierarchy remains Hierarchy. *Team_Learn_Knowledge* proceeds similarly, except that the variable distinguishes between knowledge sharing conditions (e.g., 1 – knowledge sharing not supported remaining knowledge sharing not supported, and so forth). *Team_Learn_Structure_Knowledge* represents the various possible combinations of information processing structure and knowledge within the experimentation, with each combination assigned a unique code.

b. Dependent Variables

Similar to the independent variables, the dependent variables for learning at the team level parallel the dependent variables at the individual level of analysis. To test the hypotheses about team learning, I add two dependent scalar dimensionless variables to the SPSS worksheet. *Team_Learn_Time* represents the difference in mean performance for time between consecutive plays of ELICIT by any given team. Similarly, *Team_Learn_Accuracy* represents the difference in mean performance for accuracy between consecutive plays of ELICIT by any given team.

5. List of Variables

For reference, I include a table of my independent variables and measures of dependent constructs used for subsequent analysis in Table 13 below.

	Variable Type	Coding
Individual Performance		
<i>Structure</i>	Nominal	1 – Edge information processing structure 2 – Hierarchy information processing structure
<i>Knowledge</i>	Nominal	1 – Knowledge sharing not supported 2 – Knowledge sharing supported
<i>Time</i>	Scalar	0 to 1, based on Eq. (1)
<i>Accuracy</i>	Scalar	0 to 1, based on accuracy of subject response (see Appendix C)
Individual Learning		
<i>Learn_Structure</i>	Nominal	1 – Edge to Edge 2 – Edge to Hierarchy 3 – Hierarchy to Hierarchy 4 – Hierarchy to Edge
<i>Learn_Knowledge</i>	Nominal	1 – Knowledge sharing not supported remains knowledge sharing not supported 2 – Knowledge sharing not supported changes to knowledge sharing supported 3 – Knowledge sharing supported remains knowledge sharing supported 4 – Knowledge sharing supported changes to knowledge sharing not supported
<i>Learn_Time</i>	Scalar	$\Delta Time$ since individual's previous experimental session
<i>Learn_Accuracy</i>	Scalar	$\Delta Accuracy$ since individual's previous experimental session
Team Performance		
<i>Structure</i>	Nominal	1 – Edge information processing structure 2 – Hierarchy information processing structure
<i>Knowledge</i>	Nominal	1 – Knowledge sharing not supported 2 – Knowledge sharing supported
<i>Team_Time</i>	Scalar	Mean of <i>Time</i> for subjects assigned to a team during a particular experimental session, including zeroes for subjects who fail to respond
<i>Team_Accuracy</i>	Scalar	Mean of <i>Accuracy</i> for subjects assigned to a team during a particular experimental session, including zeroes for subjects who fail to respond
Team Performance under Structural Transformation		
<i>Team_Transformation</i>	Nominal	2 – Edge to Hierarchy 4 – Hierarchy to Edge

	Variable Type	Coding
<i>Team_Transformation_Time</i>	Scalar	Δ <i>Team_Time</i> since team's previous experimental session
<i>Team_Transformation_Accuracy</i>	Scalar	Δ <i>Team_Accuracy</i> since team's previous experimental session
Team Learning		
<i>Team_Learn_Structure</i>	Nominal	1 – Edge to Edge 3 – Hierarchy to Hierarchy
<i>Team_Learn_Knowledge</i>	Nominal	See <i>Learn_Knowledge</i>
<i>Team_Learn_Time</i>	Scalar	Δ <i>Team_Time</i>
<i>Team_Learn_Accuracy</i>	Scalar	Δ <i>Team_Accuracy</i>

Table 13. Independent Variables and Measures of Dependent Variables

C. CHARACTERISTICS OF THE DEPENDENT VARIABLES

In this section, I discuss important characteristics of the dependent variables (i.e., *Time* and *Accuracy*) used to assess performance of the subjects throughout the experimentation, as well as important characteristics of the dependent variables (i.e., *Learn_Time* and *Learn_Accuracy*) used to assess learning at the individual level of analysis, in turn. I then discuss important characteristics of the dependent variables for team performance (i.e., *Team_Time* and *Team_Accuracy*) and team learning (i.e., *Team_Learn_Time* and *Team_Learn_Accuracy*). I begin by providing a basic overview of the data, and then I discuss results for tests of normality, homoskedasticity, and correlation among the dependent variables.

1. Individual Performance

As discussed in the previous chapter, the manipulation sequence (see Table 10) divides the 69 subjects into four experimental groups of approximately 17 persons per session, with absences and/or fewer than the requisite 17 players managed via a protocol applied consistently throughout the experimentation. The subjects' performance (i.e., the dependent variables of time and accuracy) can thus be grouped according to either or both of the two manipulations. Among all 210 responses, time ranges from 0.05 to 0.87 ($\mu = 0.404$, $\sigma = 0.199$) while accuracy ranges from 0.00 to 1.00 ($\mu = 0.677$, $\sigma = 0.287$). These values are roughly similar when the 24 cases in which no response is given (and

thus the subject is credited with zeroes for both time and accuracy) are included in the descriptive statistics. Inclusion of such cases depresses the means slightly, as well as increases the variance within the responses. When non-responses are included in the analysis, time ranges from 0.00 to 0.87 ($\mu = 0.362$, $\sigma = 0.225$) and accuracy ranges from 0.00 to 1.00 ($\mu = 0.604$, $\sigma = 0.341$).

a. Normality

The two components of the dependent variable *performance* (i.e., time and accuracy) are checked for normality using the Kolmogorov-Smirnov test for normality (Lilliefors 1967). As evidenced in Table 14 below, the data are not normally distributed. Standard mathematical transformations—such as log, cube, square root, reciprocal and reciprocal square root (Field 2005) fail to produce normal distributions, suggesting that non-parametric evaluations will be required (Kerlinger & Lee 2000; Field 2005) to assess comparative performance between and among individuals and teams. Rank transformations (Siegel 1957; Conover & Iman 1981; Conover & Iman 1982) are commonly used for such analysis and thus will form the basis for the results of the quantitative methods presented when examining individual performance.

	Kolmogorov-Smirnov ^a		
	Statistic	df	Sig.
<i>Time</i>	.053	210	.200
<i>Accuracy</i>	.172	210	.000
<i>Time (includes non-response as zero)</i>	.070	234	.008
<i>Accuracy (includes non-response as zero)</i>	.174	234	.000

Table 14. Results of Tests for Normal Distribution of Dependent Variables

b. Homoskedasticity

The two dependent variables – time and accuracy – are also assessed for homoskedasticity using Levene’s test (Field 2005), as grouped independently by the two primary manipulations – information processing structure and knowledge sharing. Using the 210 cases in which the subjects provided identification about the impending terrorist

attack and grouping by information processing structure (e.g., Edge and Hierarchy), Levene's test is not significant for time ($p > 0.10$) but is significant for accuracy ($p < 0.05$). These results suggest that the time data are homogeneously variant while the accuracy data are heterogeneously variant. For knowledge sharing, Levene's test is significant for both dependent variables, time ($p < 0.001$) and accuracy ($p < 0.05$), indicating that the assumption of homogeneous variance is not tenable. Results are similar if the 24 cases with no answers are also included in the analysis. For information processing structure, Levene's test suggests time as homogeneously variant ($p > 0.10$) and accuracy as heterogeneously variant ($p < 0.05$) when the additional 24 "non-answer" cases are included. For knowledge sharing, Levene's test suggests time as heterogeneously variant ($p < 0.05$) and accuracy as the same ($p < 0.01$) when the additional 24 cases are included.

c. Correlation of Dependent Variables

Although the literature predicts an axiomatic trade-off between time taken to complete a task and accuracy of the proffered product when undertaking complex work (Meyer et al. 1988; Elliott et al. 2001; Beersma et al. 2003), it is clear that task complexity and interdependence affect individuals differently (Ericsson & Lehmann 1996; Sparrowe et al. 2001) and that moderating variables, such as technology, may affect this relationship (Goodhue & Thompson 1995). Thus while the literature suggests that as accuracy increases, the time taken to perform a task also increases, it also suggests that this relationship may be contextualized by moderating factors. As a result, it would be imprudent to assume that the dependent variables are highly correlated without applying a quantitative test. Indeed, a one-way Kendall's tau correlation between the two dependent variables – time and accuracy – reveals that the two performance factors are *not* highly correlated ($\tau = 0.031, p > 0.10$) when the correlation is performed using 210 cases in which the subjects identified details of the terrorist attack. If the 24 cases in which the subjects failed to submit their identification of the terrorist attack are included (i.e., time and accuracy are both set at zero), however, the two performance factors are mildly correlated ($\tau = 0.231, p < 0.001$), reflecting that in all 24 cases in which

respondents did not answer, both time *and* accuracy were set to zero, creating a high correlation among those observations that influences the entire sample set.¹²

2. Individual Learning

As *Hypothesis 3a* and *Hypothesis 5a* imply, little is known about how Edge information processing structures compare to Hierarchy information structures with respect to individual learning, especially when subjected to knowledge sharing. As such, I confine the data on individual learning primarily to observations in which the subjects experience the same information processing structure and knowledge sharing condition during consecutive play of the game (i.e., *Learn_Structure_Knowledge* = 1, 2, 3 or 4). Experimental groups B and C transform information processing structures between the second and third sets of experiments, so I confine individual learning data to the change in performance between the first and second sets of experiments, as well as the third and fourth sets of experiments. This quality control provides a total of 62 observations of individual learning within consistent information processing structure and knowledge sharing conditions (time – $\mu = 0.0757$, $\sigma = 0.241$; accuracy – $\mu = 0.171$, $\sigma = 0.344$) over 36 days of experimentation. At the individual level of analysis, the Kolmogorov-Smirnov test for normality (Lilliefors 1967) indicates that learning data are not normally distributed, but Levene's test suggests that the individual learning data are homogeneously variant over all conditions. The lack of normality, however, suggests that non-parametric methods should be used to explore significant effects within the data.

3. Team Performance

The experimentation permits observation of the four experimental groups (e.g., A, B, C, and D) four times each, with experimental sessions generally occurring once a week for four weeks. The 2 x 2 mixed design provides eight opportunities to observe Edge information processing teams and eight opportunities to observe Hierarchy information processing teams. Similarly, the manipulation sequence provides eight opportunities to observe teams supported with knowledge sharing and eight opportunities

¹² Spearman's rho correlations provide similar results.

to observe teams not supported with knowledge sharing. Performance of each team is aggregated by experimental session based on performance of individuals within the group, and includes non-answers (i.e., failures to perform) as part of the aggregation. Among the 16 observations of mean performance at the team level, time data range from 0.152 to 0.640 ($\mu = 0.368$, $\sigma = 0.123$) and accuracy data range from 0.196 to 0.839 ($\mu = 0.593$, $\sigma = 0.173$). Due to the small number of samples under each combination of experimental conditions (Royston 1982; Royston 1983; Royston 1995; Conover 1999), the Shapiro-Wilk W test (1965) is used to check that the data are normally distributed within each combination of experimental conditions (i.e., Edge/Hierarchy, supported/not supported with knowledge sharing). Specifically, the normality test indicates that time ($W(4) = \{0.859, 0.965, 0.828, 0.877\}$, $p > 0.10$ for all) and accuracy ($W(4) = \{0.945, 0.792, 0.974, 0.843\}$, $p > 0.05$ for all) are normally distributed. Levene's test suggests that the data are homogeneously variant between groups for time ($F(3,12) = 1.423$, $p > 0.10$) and accuracy ($F(3,12) = 2.034$, $p > 0.10$). Additionally, the Box M test (1949), $M = 14.545$, $p > 0.10$, indicates that the covariance matrices are equal. These tests suggest that use of MANOVA for an initial exploration of team performance is appropriate.

4. Team Learning

The 16 experimental sessions provide eight opportunities to observe learning at the team level of analysis when subjected to *consistent* experimental conditions within a counterbalanced design. One observation per team is available between the first and second sets of experiments, and one observation per team is available between the third and fourth sets of experiments. Observations between the second and third sets of experimentation are excluded because experimental groups B and C switch structural archetypes at this point in the experimentation. The data related to the structural transformation of Teams B and C are more representative of how teams perform upon being subjected to major structural transformations (i.e., *Hypothesis 2*) and are less representative of how consistent information processing structure and/or knowledge sharing conditions influence team learning. They are discussed in the next section.

Within these eight observations of team learning, team improvement with respect to time (i.e., identifying details about the terrorist attack more quickly) ranges from -0.10 to 0.24 ($\mu = 0.084$, $\sigma = 0.128$). Negative values indicate that the team worked more slowly than its previous session, and positive values indicate that the team worked more quickly than its previous session. Team improvement with respect to accuracy (i.e., the level of accuracy associated with identifying details about the terrorist attack) ranges from 0.02 to 0.47 ($\mu = 0.163$, $\sigma = 0.144$). Positive values indicate that the team submitted more accurate responses, on average, than during the previous experimental session, although in some cases, the improvement appears negligible. Tests for normality, homoskedasticity, and homogeneity of covariance are not included as too few observations are available for analysis under each combination of conditions. Kendall's tau test suggests that the dependent variables of learning time and learning accuracy are not highly correlated at the team level of analysis.

5. Team Performance under Structural Transformation

Hypothesis 2 predicts that changes in a team's information processing structure will influence team performance. As experimental groups B and C play the ELICIT game subject to either the Edge or the Hierarchy information processing structures twice before switching to the alternate archetype, the experimentation provides an opportunity to observe the influence structural transformation (i.e., Edge to Hierarchy and Hierarchy to Edge) bi-directionally. At the team level, one observation is available under each directional transformation, suggesting that the results are useful for comparative analysis but not statistical techniques.

D. AN INITIAL LOOK AT THE DATA VIA MULTIVARIATE ANALYSIS

The experimentation involves two primary manipulations – information processing structure (i.e., Edge, Hierarchy) and knowledge sharing (i.e., supported, not supported) – and two dependent variables (i.e., performance dimensions of time and accuracy). As such, multivariate investigations generally serve as the appropriate first step for gauging whether any of the four quadrants of the basic research design produced

discernible effects at the individual and team levels of analysis (Field 2005). Multivariate investigations thus serve as a promising indicator of whether more detailed investigations are warranted. In this section, I briefly summarize the results of multivariate analysis for performance and learning at both levels of analysis.

1. Individual Level of Analysis

In this section, I concentrate on results of initial multivariate investigations for individual performance and individual learning, in turn.

a. Individual Performance

Individual performance is observed under four conditions: Edge moderated by knowledge sharing (E-K); Edge *not* moderated by knowledge sharing (E-nK); Hierarchy moderated by knowledge sharing (H-K); and Hierarchy *not* moderated by knowledge sharing (H-nK). *Hypotheses 1a* and *4a* predict that varying either the information processing structure or knowledge sharing condition will influence individual performance when completing complex, interdependent tasks, and generally speaking, MANOVA is the most useful technique for initially exploring the data. When the dependent variables of time and accuracy are not substantially correlated (as is the case with this experimentation), separate analyses of variances (ANOVAs) can be used to investigate statistical significance, with levels of significance adjusted for family-wise errors (Kerlinger & Lee 2000). Further, given that the performance data at the individual level of analysis are non-parametric and the dependent variables are not substantially correlated, the Kruskal-Wallis (1952) test, a non-parametric parallel to ANOVA, is an appropriate first step for determining whether the experimental manipulations create a discernible effect (Kerlinger & Lee 2000; Gibbons & Chakraborti 2003; Field 2005).

Using the *Structure_Knowledge* variable, in which the four quadrants of the basic research design are represented (i.e., 1 – Edge without knowledge sharing (E-nK), 2 – Edge with knowledge sharing (E-K), 3 – Hierarchy without knowledge sharing (H-K), and so forth), the Kruskal-Wallis (1952) test suggests that further investigation is warranted. As predicted by the hypotheses, both time ($H(3) = 52.1, p < 0.001$) and

accuracy ($H(3) = 10.487, p < 0.05$) reflect significant effects.¹³ Notably, however, the Kruskal-Wallis (1952) test does not indicate the experimental condition or set of conditions that create these effects; it suggests only that significant effects are noted as influencing individual performance. More detailed investigation is deferred to subsequent chapters, and results of the Kruskal-Wallis (1952) test are detailed in Table 15 below. For most samples of $N \geq 5$, the Kruskal-Wallis H test approximates the Chi-Square distribution (Field 2005).

	Time	Accuracy
Chi-Square	52.129	10.487
Df	3	3
Asymp. Sig.	.000	.015

Table 15. Kruskal-Wallis Test for Effects on Individual Performance

b. Individual Learning

Similar to hypotheses associated with individual performance, hypotheses associated with individual learning (3a and 5a) predict that varying conditions of information processing structure or knowledge sharing will influence learning when individuals undertake complex, interdependent tasks. Like performance, learning at the individual level of analysis is observed under four conditions of interest (i.e., Edge not supported by knowledge sharing, Edge supported by knowledge sharing, Hierarchy not supported by knowledge sharing, and Hierarchy supported by knowledge sharing). The Kolmogorov-Smirnov test for normality (Lilliefors 1967) indicates that the individual learning data are not normally distributed within the four conditions of interest. The learning data at the individual level of analysis are, however, homogeneously variant over all four conditions, suggesting that the Kruskal-Wallis (1952) test is again appropriate for determining whether more detailed investigation is useful (Conover 1999; Gibbons & Chakraborti 2003; Field 2005). Using the Kruskal-Wallis test (1952), time ($H(3) =$

¹³ The Kruskal-Wallis test involves a rank-sum transformation (Conover & Iman 1981; Conover & Iman 1982) and then compares group means. A similar test exists to compare medians (Field 2005). When this test was applied to the data, similar results are noted.

10.685, $p < 0.05$) reflects significant effects, but accuracy ($H(3) = 4.851$, $p > 0.10$) does not. The results are summarized in Table 16 below.

	Time	Accuracy
Chi-Square	10.685	4.851
df	3	3
Asymp. Sig.	.014	.183

Table 16. Kruskal-Wallis Test for Effects on Individual Learning

2. Team Level of Analysis

In this section, I discuss initial results for team performance and team learning, in turn. I then discuss how transformation of the information processing structures (i.e., Edge to Hierarchy, Hierarchy to Edge) impacts team performance.

a. Team Performance

Team performance is observed under four conditions – Edge information processing structure 1) supported by and 2) not supported by knowledge sharing and Hierarchy information processing structure 3) supported by and 4) not supported by knowledge sharing. *Hypotheses 1* and *4* predict that varying either of these conditions influences team performance. Despite small sample sizes (four observations of team performance under each combination of information processing structure and knowledge sharing condition), the MANOVA results are promising. Pillai's trace (Pillai 1955; Olson 1976) indicates significant effects at $p < 0.05$. Further exploration is required to investigate the source of these significant differences, but the MANOVA suggests that such investigations are warranted.

Effect	Multivariate Method	Value	F	Hypothesis df	Error df	Sig.
Information Processing Structure and Knowledge Sharing	Pillai's Trace	.425	4.067	2	11	.048

Table 17. MANOVA for Team Performance

b. Team Learning

Team learning is observed under four conditions: 1) consecutively subjected to the Edge information processing structure supported by and 2) not supported by knowledge sharing, 3) consecutively subjected to the Hierarchy information processing structure supported by and 4) not supported by knowledge sharing. As summarized in Table 18 below, some interesting main and interaction results emerge from the team learning data. Specifically, knowledge sharing appears to moderate the relationship between the Edge information processing structure and team learning differently than knowledge sharing moderates the relationship between Hierarchy information processing structure and team learning.

		Edge to Edge			Hierarchy to Hierarchy		
		μ	σ	N	μ	σ	N
With knowledge sharing	Time	.205	.053	2	.064	.208	2
	Accuracy	.075	.007	2	.210	.042	2
Without knowledge sharing	Time	-.038	.092	2	.105	.007	2
	Accuracy	.320	.212	2	.045	.035	2

Table 18. Team Learning by Information Processing Structure and Knowledge Sharing¹⁴

Despite indicators that team learning may be influenced by information processing structure and knowledge sharing, a Kruskal-Wallis test suggests significant effects for neither time ($H(3) = 4.167, p > 0.10$) nor accuracy ($H(3) = 6.667, p > 0.10$), as summarized in Table 19.

	Time	Accuracy
Chi-Square	4.167	5.777
df	3	3
Asymp. Sig.	.244	.123

Table 19. Kruskal-Wallis Test for Effects on Team Learning

¹⁴ Accuracy data in this table has been adjusted to reflect that ELICIT version 2 (used in the third session with each of the experimental groups) was more symbolically complex than the other three ELICIT variants. The data presented here reflect the relaxed criteria applied to assessing respondent accuracy, as illustrated in Appendix C: Operationalization of Accuracy, Table 49.

Given the small sample size associated with the team learning data, we cannot dismiss the results out of hand as being unimportant, despite their lack of statistical significance. Rather, the data suggest that the combination of information processing structure and knowledge sharing may uniquely influence team learning, particularly for accuracy.

c. Team Performance under Structural Transformation

The experimental design offers an opportunity to examine the influence of transforming a team from an Edge structure to a Hierarchy structure, and vice versa, on team performance. The initial results (see Table 20 below) indicate that the *direction* of the transformation (i.e., Edge to Hierarchy vs. Hierarchy to Edge) affects performance very differently. Specifically, transforming from Hierarchy *to* Edge results in improved performance for time, with no degradation in accuracy. Transforming from Edge to Hierarchy, however, results in degradation in performance for both dependent variables – i.e., time and accuracy. In effect, the team that transforms from Hierarchy to Edge maintains the same level of accuracy, but works more quickly, excelling despite the structural transformation. Team performance degrades for the team that transforms from Edge to Hierarchy. Not only does this team that transforms from Edge to Hierarchy work more slowly, but the team also produces less accurate work after the transformation.

	Edge to Hierarchy		Hierarchy to Edge	
	<i>Observed value</i>	<i>N</i>	<i>Observed value</i>	<i>N</i>
<i>Time</i>	-0.350	1	0.237	1
<i>Accuracy</i>	-0.230	1	0.000	1

Table 20. Team Performance by Directional Transformation of Information Processing Structure

E. SUMMARY

In this chapter, I provided an overview of the data collected during experimentation and articulated how data exceptions are handled in subsequent coding and analysis. I defined and classified (i.e., nominal, scalar) the independent and

dependent variables important for subsequent analysis, focusing particularly on the two manipulations embedded within the experimentation as well as measures associated with the dependent variables – i.e., individual performance, individual learning, team performance and team learning. I briefly reviewed methods for aggregating data collected at the individual level of analysis to team level measures, and I articulated my procedure for coding performance and learning data at this collective level. In order to identify statistical techniques most appropriate for analyzing the experimental data and consistent with a 2x2 mixed research design, I carefully assessed issues of normality, homoskedasticity, and homogeneity of covariance that serve as important underlying assumptions for multivariate statistical analysis. These tests are summarized in Table 21 below.

	Normal Distribution	Homogeneously Variant across Experimental Conditions	Statistically Significant Effect Indicated	Test
Individual Performance				
<i>Time</i>	No	Yes	Yes, $p < 0.001$	Kruskal-Wallis test
<i>Accuracy</i>	No	No	Yes, $p < 0.05$	Kruskal-Wallis test
Individual Learning				
<i>Time</i>	No	Yes	Yes, $p < 0.05$	Kruskal-Wallis test
<i>Accuracy</i>	No	Yes	No	Kruskal-Wallis test
Team Performance				
<i>Time</i>	Yes	Yes	Yes	MANOVA
<i>Accuracy</i>	Yes	Yes	Yes	MANOVA
Team Learning				
<i>Time</i>	Unk.	Unk.	No	Kruskal-Wallis test
<i>Accuracy</i>	Unk.	Unk.	No, but pattern of interaction of independent variables suggests further investigation	Kruskal-Wallis test
Team Performance under Structural Transformation				
<i>Time</i>	Unk.	Unk.	N/a, but direction of transformation appears to uniquely influence performance	n/a
<i>Accuracy</i>	Unk.	Unk.	N/a, but direction of transformation appears to uniquely influence performance	n/a

Table 21. Summary of Tests for Normality, Homoskedasticity, and Indications of Statistically Significant Effects for Dependent Variable Measures

Satisfied that the data could be usefully investigated using MANOVA (e.g., Bray and Maxwell 1985) or Kruskal-Wallis (1952) tests, I reported the results of initial investigations of the data. The analyses revealed that for individual performance and team performance, manipulations of the independent variables of information processing structure and knowledge sharing create statistically significant effects. For individual learning, the multivariate analysis revealed that manipulation of the independent variables influenced the time necessary to complete the task. For team learning, influence of manipulating the independent variables did not prove statistically significant for either measure of performance, but the results suggest that the interaction of independent variables produces a noticeable, organizationally significant effect that warrants further discussion. Finally, transforming from Edge to Hierarchy, and vice versa, results in asymmetric performance outcomes for the teams involved. Transforming from Edge to Hierarchy appears to significantly degrade performance, while transforming from Hierarchy to Edge seems to significantly improve performance. These results are discussed in greater detail in the chapters to follow.

V. MAIN EFFECTS

In the previous chapter, I discussed my schema for coding the independent and dependent variable data, and I highlighted various quality controls enacted during data coding. I checked that the experimentation as implemented was consistent with the experimental research design as proposed, and I articulated my technique for aggregating data collected at the individual level of analysis into team level measures. I examined the dependent variable data in detail to assess the normality of their distributions and homogeneity of their variances relative to the experimental conditions under which they were collected. Since these characteristics serve as important assumptions for various statistical tests, the examinations assisted me in determining the most appropriate statistical techniques for analyzing the dependent variable data. Via correlations and discriminant analysis, I discovered that the dependent measures of time and accuracy are not highly correlated under any of the dependent variable constructs – i.e., individual performance, individual learning, team performance, and team learning – of interest within the hypotheses. This lack of correlation within the dependent measures supports use of ANOVA and similar non-parametric techniques for exploring the main and interaction effects of varying the independent variables – i.e., information processing structure and knowledge sharing – on observed performance.

In this chapter, I explore the main effects of the experimental manipulations on individual performance, individual learning, team performance and team learning. I concentrate first on the influence of information processing structure on these four performance constructs. I then turn to the influence of knowledge sharing on the same. Hypotheses under test during each investigation are explicitly identified, and the results of all analyses are summarized at the end of the chapter. Readers more interested in the results of the hypothesis testing than the specific statistical analyses used to derive the findings may wish to skip to the discussion of the findings at the end of the chapter.

A. INFORMATION PROCESSING STRUCTURE

In this section, I describe the results for the hypotheses motivated in Chapter II on the effect of information processing structures on performance and learning at both the individual and team levels of analysis.

1. Individual Level of Analysis

In evaluating the influence of information processing structures on individual performance and learning, I begin with the former.

a. Individual Performance

Hypothesis 1a predicts that individuals operating within Edge information processing structures will outperform similar individuals operating within Hierarchy information processing structures when undertaking complex and interdependent tasks. To test this hypothesis, it is appropriate to compare the means of responses from the two groups (i.e., Edge and Hierarchy) and assess whether any observed differences are statistically significant (Field & Hole 2003; Field 2005). Non-parametric tests are most appropriate since the performance data violate assumptions of normality and homoskedasticity (Siegel 1957).

The mean time for players working within Edge configurations is 0.465. This result contrasts with the mean time of 0.333 for players working within Hierarchy configurations, suggesting that subjects in Hierarchy configurations identified the terrorist attack details *more slowly* than their Edge counterparts.¹⁵ (Recall that for both dependent variable measures, 1.0 represents best possible performance while 0.0 represented worst possible performance). This result is consistent with the hypothesis. Similarly, the mean accuracy for players working within Edge configurations is 0.694, while the mean accuracy for players working within Hierarchy configurations is 0.658.

¹⁵ To convert from the normalized scale to seconds, one would multiply by 3896 seconds. Thus the difference in time between Edge and Hierarchy is $(0.465 - 0.333) * 3896 = 514$ seconds, ~ 8.6 minutes. Thus, on average, Hierarchy groups require 8.9 additional minutes to complete the task over Edge counterparts, with a total task period of 39 to 65 minutes.

This difference is minor, but is also consistent with the hypothesis that individuals working within Edge configurations outperform individuals working within Hierarchy configurations. The data thus suggest that individuals operating within Edge information processing structures complete their work more quickly than their Hierarchy counterparts. Individuals operating within Edge structures, however, submit only slightly more accurate work than their Hierarchy counterparts. The data are summarized in Table 22.

		Information Processing Structure	
		Edge	Hierarchy
Individual Performance	Time		
	<i>Mean</i>	0.465	0.333
	<i>Median</i>	0.457	0.377
	<i>Standard Deviation</i>	0.181	0.196
	Accuracy		
	<i>Mean</i>	0.694	0.658
	<i>Median</i>	0.750	0.667
	<i>Standard Deviation</i>	0.312	0.256
<i>N</i>		112	98

Table 22. Effect of Information Processing Structure on Individual Performance

An error bar graph with 95% confidence intervals around the means of the dependent variables suggests that that relative to information processing structures, time (blue/solid) may vary significantly while accuracy (green/dashed) does not (Figure 9). Specifically, the confidence intervals confirm the initial analysis that individuals working within Edge information processing structures complete their work *more quickly* than their Hierarchy counterparts, but do not produce discernibly more accurate results.

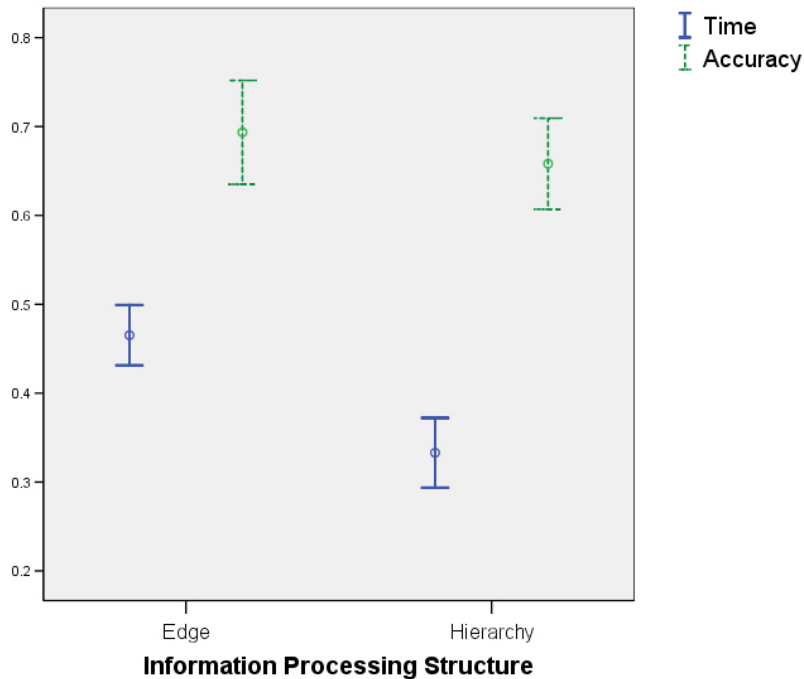


Figure 9. 95% Confidence Intervals around Dependent Variable Means -- Information Processing Structure vs. Individual Performance¹⁶

To test whether performance differences between individuals operating within the Edge and those operating within the Hierarchy (see Table 22) are significant, I use the Mann-Whitney U (1947) and Wilcoxon W (1945) rank-sum tests. These tests offer non-parametric equivalents of the independent t -test commonly used to compare means when data are parametric (Field 2005). For time, the difference is statistically significant with a medium effect ($U = 3475.0$, p (one-tailed) < 0.001 , $r = -0.32$). For accuracy, the difference is not statistically significant and only a small effect is noted ($U = 4787.5$, p (one-tailed) > 0.05 , $r = -0.11$).

An effect size reflects the influence of an experimental manipulation (e.g., Edge, Hierarchy) on the observed dependent variable (e.g., time, accuracy) by standardizing the test statistic (e.g., value obtained using Mann-Whitney U test; value

¹⁶ In this error bar chart and others to follow, the error bars do not directly align about the independent variable (e.g., Edge, Hierarchy) as doing so may create overlaps within the error bars that make the figures difficult to interpret. The error bars for Edge (time – blue/solid, accuracy – green/dashed) appear on the left side of the figure, while the error bars for Hierarchy appear on the right side of the figure.

obtained using Wilcoxon W test) to a significance test using a known distribution (e.g., χ^2 , Z , t ; see Rosenthal 1991). The significance of Mann-Whitney U test statistic and similar non-parametric techniques (e.g., Wilcoxon W) are straightforwardly approximated using z -scores (Field 2005 p. 532). Analogous with parametric methods, effect size (r) can then be calculated by:

$$r = \frac{Z}{\sqrt{N}} \quad \text{Eq. (2) (Field 2005 p. 532)}$$

As calculated using Eq. (2) above, r can be interpreted as an equivalent to the Pearson correlation coefficient for linear least-squares regression (Field 2005), in which the Pearson correlation coefficient r represents the magnitude of the linear least-squares relationship between two variables X and Y . Although arbitrary (Conover 1999), convention suggests that effect sizes of $0.10 \leq |r| < 0.30$ be considered small, effect sizes of $0.30 \leq |r| < 0.50$ be considered medium, and effect sizes of $|r| \geq 0.50$ be considered large (Cohen 1988; Cohen 1992; Field 2005). Details of the mean comparisons are captured in Table 23 below.

	Time	Accuracy
Mann-Whitney U	3475.000	4787.500
Wilcoxon W	8326.000	9638.500
Z	-4.582	-1.628
Asymp. Sig. (2-tailed)	.000	.104
Effect Size (r)	-0.32	-0.11

Table 23. Mann-Whitney Test for Information Processing Structure vs. Individual Performance

The analysis reveals that individuals operating within Edge teams complete the complex, interdependent task *more quickly* than individuals operating within teams configured as Hierarchy, and moreover, that this difference is statistically significant. This finding is consistent with the hypothesis as stated. However, while the accuracy of individuals operating within Edge teams is slightly higher than the accuracy of individuals operating within Hierarchy teams, this difference is slight, and not statistically significant. This finding is not consistent with the hypothesis, which predicts

that individuals within Edge teams outperform individuals within Hierarchy teams. *Hypothesis 1a* is thus partially supported (i.e., supported for time, but not for accuracy).

Both the Mann-Whitney (1947) and Wilcoxon (1945) rank-sum tests assume independent observations. Since some subjects repeat the experiment (using different versions of the ELICIT game) during subsequent sessions, it is prudent to check whether the significant differences noted above hold for each round of experimentation (e.g., during all experimentation with ELICIT version 1, all experimentation with ELICIT version 2, etc). The total sample size for each group (i.e., Edge vs. Hierarchy) is relatively small when the data are examined by experimental round, so the Kolmogorov-Smirnov Z test is most appropriate (Shephard & Martz 2001; Field 2005).

The Kolmogorov-Smirnov Z results for all four rounds of experimentation (see Table 24) confirm that generally speaking, individuals operating within an Edge configuration complete the task more quickly than those within a Hierarchy configuration, and that the differences related to how quickly the task is completed are statistically significant. However, while individuals operating within an Edge configuration produce slightly more accurate work than their Hierarchy counterparts, these differences are not statistically significant. Analyzing the data by experimental round thus offers further evidence that *Hypothesis 1a* is partially supported. The effect sizes are generally small (i.e., $0.09 < r < 0.27$), but are consistent with the hypothesis – i.e., individuals operating within Edge information processing structures outperform those operating within Hierarchy information processing structures, especially in terms of completing work more quickly.

		Time	Accuracy
Round 1	Kolmogorov-Smirnov Z	1.128	.741
	Asymp. Sig. (2-tailed)	.157	.643
	N	50	50
	Effect size (<i>r</i>)	0.16	0.10
Round 2	Kolmogorov-Smirnov Z	2.027	1.362
	Asymp. Sig. (2-tailed)	.001	.049
	N	57	57
	Effect size (<i>r</i>)	0.27	0.18
Round 3	Kolmogorov-Smirnov Z	1.324	.670
	Asymp. Sig. (2-tailed)	.060	.761
	N	53	53
	Effect size (<i>r</i>)	0.18	0.09
Round 4	Kolmogorov-Smirnov Z	1.385	.840
	Asymp. Sig. (2-tailed)	.043	.481
	N	50	50
	Effect size (<i>r</i>)	0.20	0.12

Table 24. Kolmogorov-Smirnov Z Test for Information Processing Structure vs. Individual Performance

b. Individual Learning

Similar to the hypothesis regarding the influence of information processing structure on performance, *Hypothesis 3a* predicts that individuals working within Edge teams learn more quickly than individuals working within Hierarchy teams. To test this hypothesis, I examine the differences in performance when a subject plays ELICIT consecutively while subjected to Edge information processing structures (time: $\mu = 0.125$, $\sigma = 0.221$, $N = 32$; accuracy: $\mu = 0.223$, $\sigma = 0.367$, $N = 32$) against differences in performance when a subject plays ELICIT consecutively while subjected to Hierarchy information processing structures (time: $\mu = 0.024$, $\sigma = 0.254$, $N = 30$; accuracy: $\mu = 0.116$, $\sigma = 0.316$, $N = 30$).

Simple examination of the data suggests that individual learning is indeed enhanced when working within Edge teams. When assigned to Edge teams, individuals improve their time by an average of 0.125. Put differently, subjects complete the task about 8.1 minutes *faster* than the previous experimental session when assigned to Edge teams. In contrast, when assigned to Hierarchy teams, individuals improve their time, on average, by only 0.024, or about 1.6 minutes faster than previous experimental session.

In both types of teams (i.e., Edge and Hierarchy), individuals learn how to complete their work more quickly. However, the data suggest that for individuals, the rate of learning (in terms of the time needed to complete one's work) is higher when assigned to Edge information processing structures than when assigned to Hierarchy information processing structures. This initial comparison is consistent with the stated hypothesis (i.e., individuals within Edge structures learn more quickly than individuals within Hierarchy structures).

For accuracy, a similar pattern emerges. Specifically, individuals working within Edge information processing structures improve the accuracy of their work by an average of 0.223 over the previous experimental session. Individuals operating within Hierarchy information processing structures improve the accuracy of their work by an average of 0.116. Individuals learn how to produce more accurate work under both information processing conditions, but the rate of learning is higher for individuals assigned to Edge structures. This result is also consistent by the hypothesis as given.

The Kolmogorov-Smirnov (Lilliefors 1967) test for normality indicates that the individual learning data are not normally distributed. Specifically, for individuals working within Edge information processing structures, improvements in time are normally distributed ($D(32) = 0.079, p > 0.10$) and improvements in accuracy are not normally distributed ($D(32) = 0.178, p < 0.05$). For individuals working within Hierarchy information processing structures, improvements in time ($D(30) = 0.189, p < 0.01$) are not normally distributed, but improvements in accuracy ($D(30) = 0.155, p > 0.05$) are normally distributed. Levene's test for homoskedasticity does suggest, however, that both time ($F(1,60) = 0.014, p > 0.10$) and accuracy ($F(1,60) = 0.197, p > 0.10$) are homogeneously variant. Nonetheless, lack of normality in the data suggests that non-parametric statistics should be used to compare individual learning within Edge structures against individual learning within Hierarchy structures (Field 2005). Table 25 summarizes the individual learning data.

		Information Processing Structure	
		Edge	Hierarchy
Individual Learning	Time		
	<i>Mean</i>	.125	.024
	<i>Median</i>	.117	.017
	<i>Standard Deviation</i>	.221	.254
	Accuracy		
	<i>Mean</i>	.223	.116
	<i>Median</i>	.250	.080
	<i>Standard Deviation</i>	.367	.316
<i>N</i>		32	30

Table 25. Effect of Information Processing Structure on Individual Learning

An error bar chart (see Figure 10) that depicts the 95% confidence intervals around the means of the dependent measure time (in blue/solid) suggests that assignment to an Edge information processing structure may enable individuals to learn how to complete one's work more quickly than similar individuals assigned to a Hierarchy information processing structure. Similarly, similar error bars around the dependent variable accuracy suggest that on average, assignment to an Edge information processing structure assists individuals with learning how to produce more accurate work (in green/dashed) over similar individuals assigned to a Hierarchy information processing structure. The results, while not conclusive, are consistent with the hypothesis as stated.

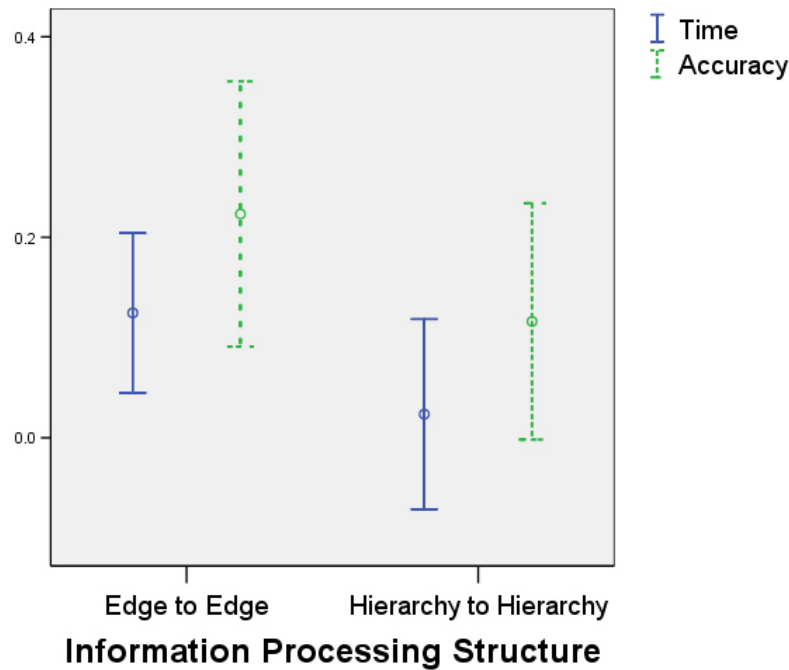


Figure 10. 95% Confidence Intervals around Dependent Variable Means -- Information Processing Structure vs. Individual Learning

Since the individual learning data are non-parametric, the Mann-Whitney (1947) test is used to determine whether the differences between mean individual learning as observed within the Edge information processing structure and mean individual learning as observed within the Hierarchy information processing structure are significant. For time, the difference is statistically significant with a small effect ($U = 344.0, p \text{ (one-tailed)} < 0.05, r = -0.24$). For accuracy, the difference is not statistically significant and a small effect is noted ($U = 383.5, p \text{ (one-tailed)} > 0.05, r = -0.17$).

	Time	Accuracy
Mann-Whitney U	344.0	383.5
Wilcoxon W	809.0	848.5
Z	-1.916	-1.370
Asymp. Sig. (2-tailed)	.055	.171
Effect Size (r)	-0.24	-0.17

Table 26. Mann-Whitney Test for Information Processing Structure vs. Individual Learning

Individuals demonstrate learning when assigned to either Edge or Hierarchy information processing structures. They learn how to complete the complex, interdependent task more quickly, as well as how to produce more accurate work. Relative to time, the rate of individual learning for persons operating within Edge information processing structures is higher than the rate of individual learning for persons operating within Hierarchy information processing structures. This finding is statistically significant and consistent with the hypothesis as stated. Relative to accuracy, the rate of individual learning for persons operating within Edge information processing structures is higher than the rate of individual learning for persons operating within Hierarchy information processing structures. However, this finding is not statistically significant. Put simply, individual learning occurs regardless of whether subjects are assigned to Edge or Hierarchy structures. Relative to completing work more quickly, individual learning within Edge teams is higher than within Hierarchy teams. However, individual learning relative to producing more accurate work, based on the experimental data, is indifferent to information processing structure. I conclude that *Hypothesis 3a* is partially supported.

2. Team Level of Analysis

In this section, I describe the results of the experimentation motivated by a subset of the team-level hypotheses articulated in Chapter II. Specifically, I focus on the influence of information processing structure on team performance and team learning. As summarized in Table 10, each experimental group plays a variant of the counterterrorism decisionmaking game four times, providing a total of 16 team-level results. Among these 16 sessions, teams are subjected to the Edge information processing structure eight times and the Hierarchy information processing structure eight times.

a. Team Performance

Hypothesis 1 predicts that when undertaking complex and interdependent tasks, Edge teams will outperform Hierarchy teams. To test this hypothesis, I examine

the difference in mean performance between Edge teams (time – $\mu = 0.418$, $\sigma = 0.111$, $N = 8$; accuracy – $\mu = 0.613$, $\sigma = 0.211$, $N = 8$) and Hierarchy teams (time – $\mu = 0.318$, $\sigma = 0.120$, $N = 8$; accuracy – $\mu = 0.573$, $\sigma = 0.138$, $N = 8$) using both measures of performance.

Cursory examination of the data suggests that on average, Edge teams work more quickly than their Hierarchy counterparts. Moreover, the work produced by Edge teams is negligibly more accurate. Both initial comparisons are consistent with the stated hypothesis. On the time dimension of performance, for example, the Edge teams average 0.418 to the Hierarchy teams' 0.318, a difference of $(0.418 - 0.318) * 3896 = 389.6$ seconds, or about 6.5 minutes during an experimental session that generally lasts about 60 minutes. (Recall that 1.0 represents best possible performance while 0.0 represents worst possible performance on both dependent variable measures.) Differences in mean accuracy also favor the Edge teams, but to a significantly lesser – indeed nearly negligible – degree ($0.613 - 0.573 = 0.04$). Initial indications thus suggest that Edge teams outperform Hierarchy teams (as predicted), but that the two dimensions of performance are impacted differently. *Edge teams work more quickly, but only negligibly more accurately, than their Hierarchy counterparts.*

Applying the Kolmogorov-Smirnov (Lilliefors 1967) test for normality indicates that the team performance data are normally distributed. Specifically, for the teams structured as Edge, mean performance on the dimensions of time ($D(8) = 0.218$, $p > 0.10$) and accuracy ($D(8) = 0.222$, $p > 0.10$) are normally distributed. For teams structured as Hierarchies, mean performance on the dimensions of time ($D(8) = 0.227$, $p > 0.10$) and accuracy ($D(8) = 0.260$, $p > 0.10$) also indicate normally distributed data. Further, Levene's test for homoskedasticity suggests that both time ($F(1,14) = 0.171$, $p > 0.10$) and accuracy ($F(1,14) = 0.429$, $p > 0.10$) are homogeneously variant. As a result, parametric methods can be used to compare Edge team and Hierarchy team performance (Field 2005). Table 27 summarizes selected descriptive statistics for assessing the influence of information processing structure (i.e., Edge vs. Hierarchy) on team performance.

		Information Processing Structure	
		Edge	Hierarchy
Team Performance	Time		
	<i>Mean</i>	0.418	0.318
	<i>Median</i>	0.376	0.353
	<i>Standard Deviation</i>	0.111	0.120
	Accuracy		
	<i>Mean</i>	0.613	0.573
	<i>Median</i>	0.632	0.525
	<i>Standard Deviation</i>	0.211	0.138
<i>N</i>		8	8

Table 27. Effect of Information Processing Structure on Team Performance

Figure 11 provides an error bar chart with 95% confidence intervals around the means of the dependent variables of time and accuracy at the team level of analysis. The error bars are differentiated by the primary manipulation of information processing structure (i.e., Edge, Hierarchy). The confidence intervals suggest that Edge teams, on average, may complete complex, interdependence tasks more quickly than Hierarchy teams (blue/solid). However, the confidence intervals suggest that on average, both Edge and Hierarchy teams will provide similarly accurate work (green/dashed).

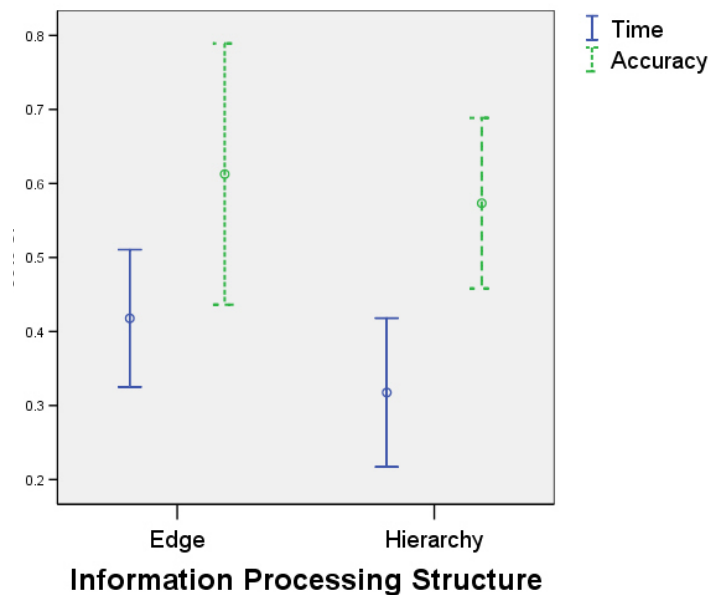


Figure 11. 95% Confidence Intervals for Means of Dependent Variables -- Information Processing Structure vs. Team Performance

The research design includes only two possibilities for information processing structure (i.e., Edge or Hierarchy). As a result, ANOVA and an independent samples *t*-test produce the same results (Field 2005) for comparing team performance, especially as the two dependent variables of time and accuracy are not correlated ($r = -0.02, p > 0.10$). The results suggest that for team performance, neither differences in time ($F(1,14) = 3.006, p \text{ (one-tailed)} > 0.05$, medium effect size) nor accuracy ($F(1,14) = 0.195, p \text{ (one-tailed)} > 0.10$, small effect size) are statistically significant. As information processing structure is a dichotomous variable (i.e., Edge or Hierarchy), effect size can be calculated using the *t* statistic for time ($t(14) = 1.734$) and accuracy ($t(14) = 0.442$), calculated through the following equation:

$$r = \sqrt{\frac{t^2}{t^2 + df}} \quad \text{Eq. (3) (Field 2005)}$$

The results are summarized in Table 28 below.

Edge vs. Hierarchy		Sum of Squares	df	Mean Square	F	Sig.	Effect size (based on <i>t</i> -test)
Mean Time (Team)	Between Groups	.040	1	.040	3.006	.105	0.42
	Within Groups	.187	14	.013			
	Total	.227	15				
Mean Accuracy (Team)	Between Groups	.006	1	.006	.195	.666	0.12
	Within Groups	.445	14	.032			
	Total	.451	15				

Table 28. Information Processing Structure vs. Team Performance (ANOVA)

These results suggest that *Hypothesis 1*, which predicted that Edge teams would outperform Hierarchy teams when undertaking complex, interdependent tasks, is not supported. On average, Edge teams appear to work much more quickly than Hierarchy teams, but the observed data do not support concluding this difference is statistically significant. Moreover, while the experimental data suggest that on average, Edge teams produce more accurate work than Hierarchy teams, this difference is not statistically significant. Indeed, as recent computational organization theorizing and

hypothesis testing (Orr & Nissen 2006; Gateau et al. 2007) has demonstrated, Edge teams may produce more volatile performance.

Although differences in mean performance between Edge and Hierarchy teams is not statistically significant, the one-tailed significance value for time ($p = 0.053$) and small sample size ($N = 16$) seems to suggest that the hypothesis should not be rejected out of hand. On average, as Table 27 demonstrates, teams with Edge information processing structures (i.e., low centralization, low formalization, and low vertical differentiation) complete their work more quickly than teams with Hierarchy information processing structures. Previous and concurrent computational modeling (Orr & Nissen 2006; Gateau et al. 2007; MacKinnon et al. 2007) indicate that enlarging the experimentation to a slightly larger sample size would likely lead to concluding that Edge teams complete their work more quickly than Hierarchy teams. Related case studies (e.g., Brown & Eisenhardt 1997) also seem to support this view. Thus I suggest that additional experimentation, possibly using an expanded variant of my theoretical model, may prove illuminating.

b. Team Performance under Structural Transformation

Hypothesis 2 predicts that transforming from an Edge to Hierarchy information processing structure, and vice versa, will influence team performance. To test this hypothesis, I switched two of the groups to alternate information processing structures between the second and third experimental session with each team. (Recall that each team participates in four experimental sessions.) Specifically, Team B completed two experimental sessions subjected to a Hierarchy information processing structure, and then completed the remaining two experimental sessions subjected to an Edge information processing structure. Team C completed two experimental sessions subjected to an Edge information processing structure, and then completed the remaining two experimental sessions subjected to a Hierarchy information processing structure.

This experimental manipulation provided an opportunity to observe effects of transformation in both directions – i.e., Edge to Hierarchy and Hierarchy to Edge – on team performance.

An insufficient sample size limits the usefulness of analyses of variance or similar methods for comparing the results, but the magnitude of difference between performance of an Edge team transformed to a Hierarchy team and a Hierarchy team transformed to an Edge team is worthy of discussion. For example, Team B, when transformed from a Hierarchy structure to an Edge structure, reduced the amount of time used to identify the terrorist attack by $0.237 * 3896 = 923$ seconds, demonstrating a 15.4 minute *improvement* in performance over the previous experimental session. Team C, on the other hand, when transformed from an Edge to a Hierarchy structure, increased the amount of time used to identify the terrorist attack by $0.350 * 3896 = 1363$ seconds, demonstrating a 22.7 minute *degradation* in performance over the previous experimental session.

Similar results are noted for the dependent variable accuracy. For example, when Team B transformed from the Hierarchy to the Edge information processing structure, Team B's accuracy remained exactly the same. When Team C transformed from an Edge to a Hierarchy information processing structure, the team's accuracy *diminished* by 0.13. These data, while clearly not conclusive, are still illuminating, and the differences are striking. The data suggest that *Hypothesis 2* – i.e., that transforming from Edge to Hierarchy and Hierarchy to Edge influences team performance – is supported. Figure 12 illustrates the change in performance for both dependent variables. Change in performance of the team transformed from Edge to Hierarchy is depicted in green (thin stripes), while change in performance of the team transformed from Hierarchy to Edge is depicted in blue (thick stripes). Note that for the team transitioning from Hierarchy to Edge (in blue/thick stripes), the change in accuracy was negligible.

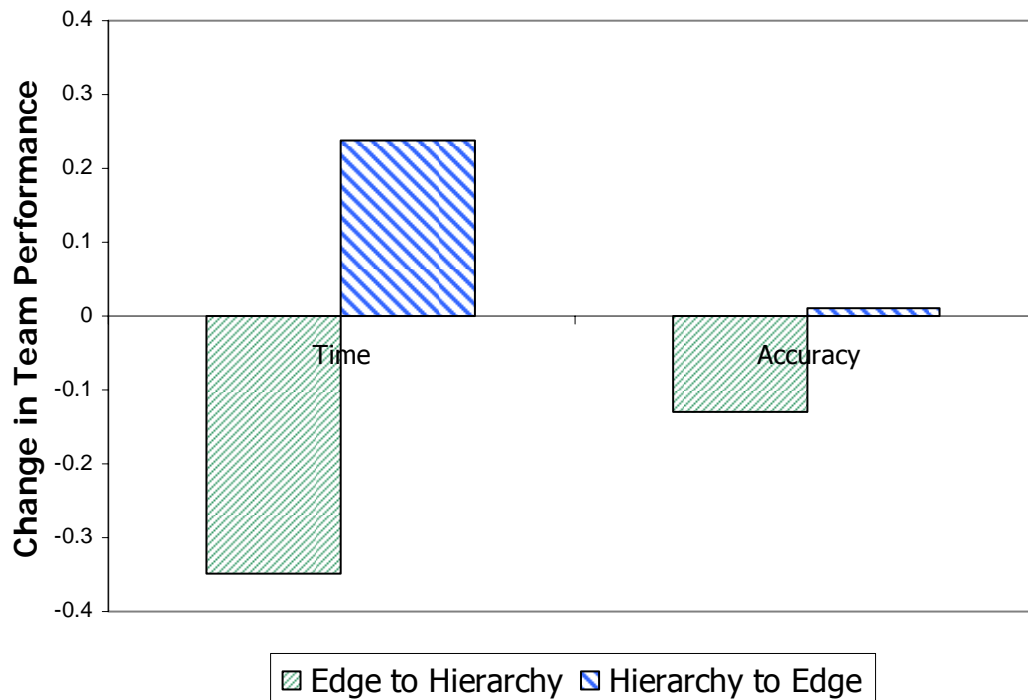


Figure 12. Change in Team Performance, Edge to Hierarchy and Hierarchy to Edge

c. Team Learning

Hypothesis 3 posits that Edge teams will learn more quickly than Hierarchy teams when undertaking complex, interdependent tasks. To test this hypothesis, I examine differences in team learning for teams playing consecutive sessions in the same information processing structures (i.e., Edge, Hierarchy) on both dimensions of performance (see Table 29 for a summary of the experimental data). Cursory examination of the data suggests that on average, the rate of learning for Edge teams, relative to time, is equal to the rate of learning for Hierarchy teams. However, Edge teams learn how to produce more accurate work at a higher rate of learning than Hierarchy teams.

For example, consider improvement in time. On average, Edge teams improve their time by 0.084 from one complex, interdependent task to the next.

Likewise, Hierarchy teams improve their time, on average, by 0.084 when undertaking equivalently complex and interdependent tasks. For both types of teams, improvement in time is roughly equal. Moreover, consider improvement in accuracy. On average, Edge teams improve their accuracy by 0.198, while Hierarchy teams improve their accuracy by 0.128. This implies that, on average, Edge teams learn how to provide results that are $0.198 - 0.128 = 0.07$ (out of 1.0) more accurate than their Hierarchy counterparts each time either type of team undertakes a complex, interdependent task. A simple comparison of the data, then, suggests that Edge and Hierarchy teams learn at about the same rate, which is inconsistent with the hypothesis that predicted Edge teams will learn more quickly than Hierarchy teams.

		Information Processing Structure	
		Edge	Hierarchy
Team Learning	Time		
	<i>Mean</i>	.084	.084
	<i>Median</i>	.098	.105
	<i>Standard Deviation</i>	.153	.122
	Accuracy		
	<i>Mean</i>	.198	.128
	<i>Median</i>	.125	.125
	<i>Standard Deviation</i>	.187	.100
	<i>N</i>	4	4

Table 29. Effect of Information Processing Structure on Team Learning

To further explore the hypothesis that Edge teams learn more quickly than Hierarchy teams, I construct an error bar chart depicting 95% confidence intervals around the means of the two dependent variables (see Figure 13) for team learning. Improvement in time is depicted in blue (solid) and improvement in accuracy is depicted in green (dashed). The error bars suggest that both Edge and Hierarchy teams learn at roughly the same rate, although the Edge learning appears to be particularly volatile for accuracy. Put simply, the error bar chart suggests that team learning, on average, *is largely indifferent* to the information processing structure imposed upon the team.

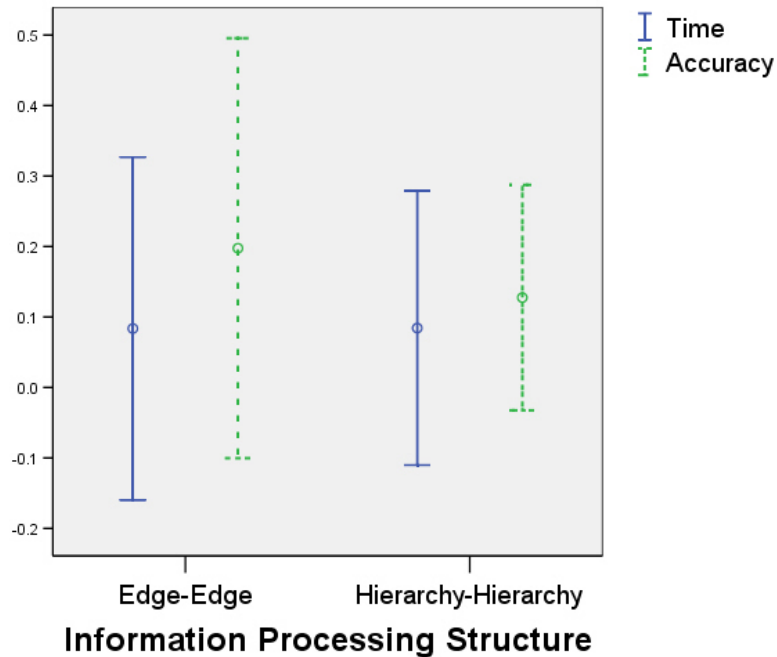


Figure 13. 95% Confidence Intervals around Dependent Variable Means -- Information Processing Structure vs. Team Learning

This conclusion – i.e., that team learning, on average, is indifferent to manipulations of the information processing structure – is verified with further statistical inquiry. The Shapiro-Wilk test suggests that team learning data are normally distributed for improvements in time (Edge - $D(4) = 0.830$, $p > 0.10$; Hierarchy - $D(4) = 0.558$, $p > 0.10$) and accuracy (Edge - $D(4) = 0.800$, $p > 0.10$; Hierarchy - $D(4) = 0.709$, $p > 0.10$). The data are also homogeneously variant for both improvements in time ($F(1,6) = 0.469$, $p > 0.10$) and accuracy ($F(1,6) = 0.351$, $p > 0.10$), allowing use of parametric methods to compare the means. An independent t -test (see Table 30) establishes that the means are comparatively equal for both dependent variables (time - $t(6) = -0.007$, p (one-tailed) > 0.10 , $r = .00$, negligible effect; accuracy - $t(6) = -0.534$, p (one-tailed) > 0.10 , $r = 0.26$, small effect).

	<i>t</i>	df	Sig. (2-tailed)	Effect size
Time (Team Learning)	-.007	6	.995	.00
Accuracy (Team Learning)	.659	6	.534	.26

Table 30. Information Processing Structure vs. Team Learning (t -statistic)

As a result, *Hypothesis 3* is not supported, and I conclude that Edge and Hierarchy teams learn how to improve their accuracy and speed at equal rates. Notably, however, when effect size is calculated using the *t*-statistic (see Equation 3) and combined with the small sample size, the analysis suggests that further investigation of the influence of information processing structure on team learning relative to accuracy may be fruitful to subsequent researchers.

B. KNOWLEDGE SHARING AS CONTINGENCY

The first three hypotheses motivated in Chapter II focused on how manipulating information processing structures might influence individual performance, individual learning, team performance and team learning. One of the hypotheses also suggested that team performance might be impacted by transforming a team's information processing structure. Various levels of support were found for the motivated hypotheses. In this section, I turn to the hypotheses focused on how manipulating knowledge sharing influences individual performance, individual learning, team performance and team learning. In discussing each relationship, I provide a detailed analysis similar to that explicated above.

1. Individual Level of Analysis

In this section, I focus upon the influence of knowledge on individual performance and learning, in turn.

a. Individual Performance

Hypothesis 4a predicts that when assigned complex and interdependent tasks, individuals operating within teams that regularly share actionable information (i.e., knowledge) will outperform individuals operating in teams that do not share actionable information (i.e., knowledge). To test this hypothesis, I compare the performance means between individuals operating within teams with knowledge sharing (time - $\mu = 0.367$, $\sigma = 0.222$, $N = 128$; accuracy - $\mu = 0.722$, $\sigma = 0.264$, $N = 128$) against those operating

within groups without knowledge sharing (time - $\mu = 0.461$, $\sigma = 0.139$, $N = 82$; accuracy - $\mu = 0.607$, $\sigma = 0.308$, $N = 82$).

The Kolmogorov-Smirnov (Lilliefors 1967) test for normality indicates that the data are not normally distributed for time either with knowledge sharing ($D(82) = 0.157$, $p < 0.001$) or without knowledge sharing ($D(128) = 0.105$, $p < 0.001$). For accuracy, the data are also not normally distributed with knowledge sharing ($D(128) = 0.167$, $p < 0.001$) or without this contingency ($D(128) = 0.189$, $p < 0.001$). Levene's test also suggests that the data are homogeneously variant for neither time ($F(1,208) = 33.274$, $p < 0.001$) nor accuracy ($F(1,208) = 5.838$, $p < 0.05$). Non-parametric tests are thus more useful (Siegel 1957; Sheskin 1997; Field 2005) for exploring the data. As stated previously, a total of 210 observations involving 69 unique subjects are collected for analysis. Table 31 summarizes these data.

Cursory examination of the descriptive statistics suggest that on average, when individuals are supported with knowledge sharing, they work *more slowly* but submit *more accurate* responses on complex, interdependent tasks. For example, consider the dependent variable time. With the support of knowledge sharing, the subjects respond with a mean time of 0.367, or after 41.1 minutes of the approximately 60 minute experimental session has elapsed. (Recall that for dependent variable measures time and accuracy, the value 1.0 represents best possible performance while 0.0 represents worst possible performance.) Without the support of knowledge sharing, the subjects respond with a mean time of 0.461, or after 35.0 minutes have elapsed. Without knowledge sharing, then, the subjects respond, on average, about seven minutes more quickly than those working with knowledge sharing. This initial comparison is contrary to the stated hypothesis.

For accuracy, however, the results differ. For individuals working in environments in which knowledge sharing is supported, the mean accuracy of the attack details is 0.722 (out of 1.0). For individuals working in environments without support of knowledge sharing, the mean accuracy is 0.607, or about 0.115 *less accurate*. This initial comparison is consistent with the stated hypothesis. Put simply, individuals working in environments supported by knowledge sharing appear to work more slowly, but also

more accurately, on complex, interdependent tasks. Individuals working in environments *not* supported by knowledge sharing appear to work more quickly, but also less accurately, on complex, interdependent tasks.

		Knowledge Sharing	
		Not supported	Supported
Individual Performance	Time		
	<i>Mean</i>	0.461	0.367
	<i>Median</i>	0.427	0.361
	<i>Standard Deviation</i>	0.139	0.222
	Accuracy		
	<i>Mean</i>	0.607	0.722
	<i>Median</i>	0.667	0.750
	<i>Standard Deviation</i>	0.308	0.264
	<i>N</i>	82	128

Table 31. Effect of Knowledge Sharing as Contingency on Individual Performance

Field (2005) suggests that error bar charts, depicting 95% confidence intervals around the means of the dependent variables, can be useful for comparative analysis. An error bar chart (Figure 14) comparing predicted means for time and accuracy under conditions of with knowledge sharing and without knowledge sharing is consistent with the cursory examination above. Specifically, the error bar chart suggests that relative to accuracy (in green/dashed), subjects in environments with knowledge sharing provide more accurate identifications of the terrorist attack (as predicted). However, opposite to the predicted effect, subjects without knowledge sharing work more slowly (in blue/solid).

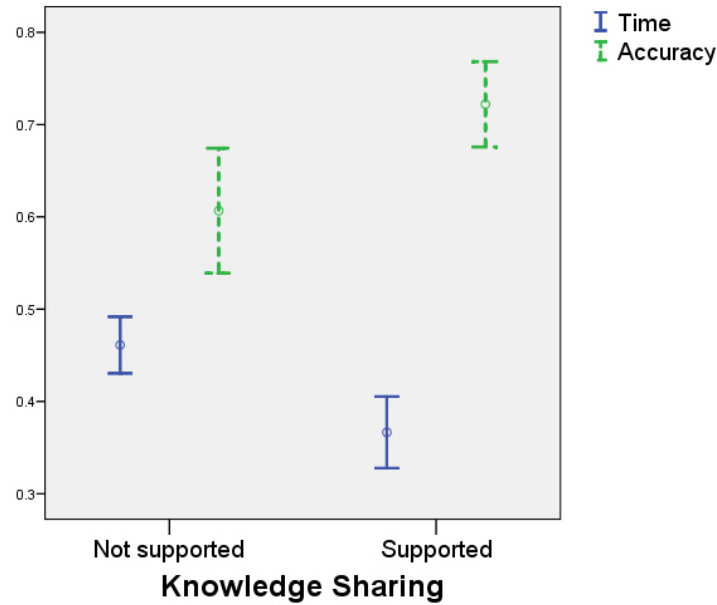


Figure 14. 95% Confidence Intervals around Dependent Variable Means – Effect of Knowledge Sharing as Contingency on Individual Performance

Mann-Whitney (1947) and Wilcoxon (1945) tests verify the cursory and graphic analysis. Specifically, these tests, which compare means of non-parametric data sets, suggest that the presence of knowledge sharing creates a statistically significant difference with a small effect for time ($U = 3844.0$, p (one-tailed) < 0.001 , $r = -0.23$). Individuals working without knowledge sharing tend to work more quickly than counterparts working with knowledge sharing. This effect is contrary to the hypothesis as stated. Consistent with predicted results, however, the presence of knowledge sharing creates a significant, but small effect for accuracy ($U = 4106.5$, p (one-tailed) < 0.01 , $r = -0.19$). *Hypothesis 4a* is partially supported – i.e., not supported for time, but supported for accuracy. The results are summarized in Table 32 below.

	Time	Accuracy
Mann-Whitney U	3844.0	4106.5
Wilcoxon W	12100.0	7509.5
Z	-3.268	-2.713
Asymp. Sig. (2-tailed)	.001	.007
Effect Size (r)	-0.23	-0.19

Table 32. Mann-Whitney Test for Influence of Knowledge Sharing as Contingency on Individual Performance

b. Individual Learning

Hypothesis 5a predicts that when assigned complex and interdependent tasks, individuals operating in teams that regularly share actionable information (i.e., knowledge) will learn more quickly than individuals operating in teams that do not regularly share actionable information (i.e., knowledge). Testing this hypothesis can be achieved by comparing the mean performance improvement of individuals working within teams that are supported with knowledge sharing against mean performance improvements of individuals working within teams that are *not* supported with knowledge sharing (see Table 33). Individual learning data for time are normally distributed whether supported or not supported by knowledge sharing (supported: $D(37) = 0.133, p > 0.05$; not supported: $(D(25) = 0.089, p > 0.10)$). However, individual learning data for accuracy are not normally distributed when knowledge sharing is supported ($D(37) = 0.194, p < 0.001$), but are normally distributed when knowledge sharing is not supported ($D(25) = 0.157, p > 0.10$). Further, individual learning data for time are heterogeneously variant ($F(1,60) = 5.932, p < 0.05$) while individual learning data for accuracy are homogeneously variant ($F(1,60) = 1.026, p > 0.10$). Non-parametric tests are thus most suitable for exploring the influence of knowledge sharing on individual learning.

Table 33 summarizes the individual learning data for time and accuracy. A perfunctory review of the data suggests that the hypothesis is supported for improvements in time, but not improvements in accuracy. Specifically, individuals participating in teams with knowledge sharing learn how to complete their work more quickly. On average, for example, individual improvements in time for subjects operating in teams supported by knowledge sharing measure 0.106. This translates into individuals completing the task approximately 6.9 minutes more quickly than their previous attempt at a similar task. In contrast, individual improvements in time, when *not* supported by knowledge sharing, average 0.031. This translates into individuals completing the task about 2.0 minutes more quickly than their previous attempts at a similar endeavor. Those operating in teams supported by and not supported by knowledge sharing *both* learn how to work more quickly. However, for those supported

by knowledge sharing, the rate of learning, relative to completing the task more quickly, is greater. This comparison is consistent with the hypothesis as stated.

In contrast, individuals assigned to teams with knowledge sharing learn how to produce more accurate work at about the same rate as individuals assigned to teams without knowledge sharing. Specifically, individual improvements in accuracy, when assigned to teams supported by knowledge sharing, average 0.175. Individual improvements for accuracy, when assigned to teams *not* supported by knowledge sharing, average 0.165. Mean improvement in accuracy for individuals assigned to teams supported by knowledge is slightly higher than mean improvement in accuracy for individuals assigned to teams not supported by knowledge sharing. This result is consistent with the stated hypothesis. However, the magnitude of the difference is negligible.

		Knowledge Sharing	
		Not supported	Supported
Individual Learning	Time		
	<i>Mean</i>	0.031	0.106
	<i>Median</i>	0.027	0.116
	<i>Standard Deviation</i>	0.147	0.286
	Accuracy		
	<i>Mean</i>	0.165	0.175
	<i>Median</i>	0.080	0.170
	<i>Standard Deviation</i>	0.359	0.339
	<i>N</i>	25	37

Table 33. Effect of Knowledge Sharing as Contingency on Individual Learning

Figure 15 depicts 95% confidence intervals around the means of the two dependent variables for assessing the influence of knowledge sharing on individual learning. As the graph illustrates, the experimental data suggest *Hypothesis 5a* is supported for improvements in time (in blue/solid), but not improvements in accuracy (in green/dashed). The graph suggests that over time and through task repetition, the learning rate for individuals working with teams that regularly share actionable information (i.e., knowledge) learn how to work more quickly (as predicted) is higher than the learning rate for individuals working within teams that do not regularly share

actionable information (i.e., knowledge). Individual learning relative to time is thus consistent with the stated hypothesis. However, being supported with knowledge sharing does not appear to influence individual learning relative to accuracy. The learning rate for individuals, whether supported or not supported with knowledge sharing, is relatively equal. This comparison is contrary to the prediction that individual learning is higher when individuals are assigned to teams supported with knowledge sharing.

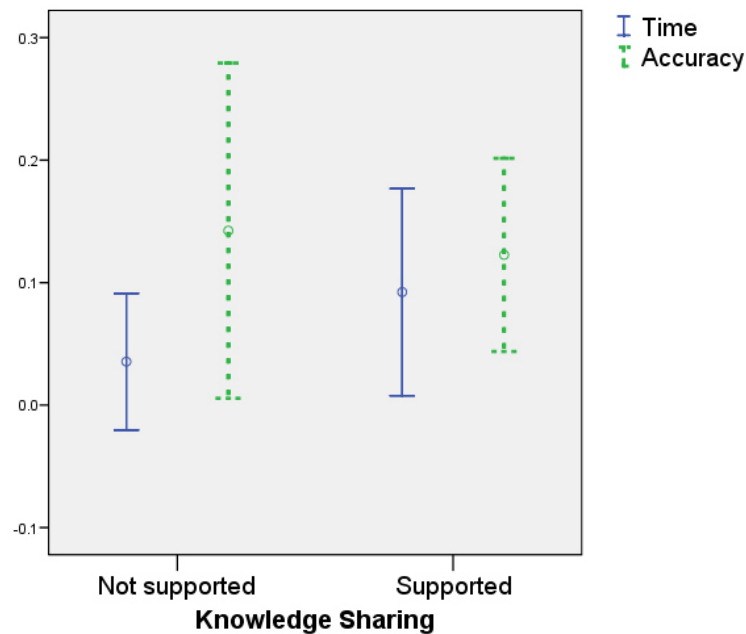


Figure 15. 95% Confidence Intervals around Dependent Variable Means – Effect of Knowledge Sharing as Contingency on Individual Learning

Since the individual learning data for time and accuracy are mixed in terms of the normality of their distributions and homogeneity of their variances, I use the Mann-Whitney (1947) and Wilcoxon (1945) tests as a final analysis for *Hypothesis 5a*. The tests (see summary in Table 34 below) suggest that for improving the speed at which they complete their work, individuals benefit most from assignment to teams supported by knowledge sharing. Moreover, the difference is statistically significant with small effect size ($U = 333.5$, p (one-tailed) < 0.05 , $r = -0.24$). Similarly, the Mann-Whitney (1947) test indicates that for improving the accuracy of individual work, either

knowledge sharing condition (i.e., supported, not supported) produces relatively equal results ($U = 426.0$, p (one-tailed) > 0.10 , $r = -0.07$). Relative to accuracy, individual learning within teams supported by knowledge is roughly similar to individual learning within teams not supported by knowledge sharing. *Hypothesis 5a* is partially supported by the experimental results – i.e., supported for time, but not supported for accuracy.

	Time	Accuracy
Mann-Whitney U	333.5	426.0
Wilcoxon W	658.5	751.0
Z	-1.851	-.528
Asymp. Sig. (2-tailed)	.064	.598
Effect Size (r)	-0.24	-0.07

Table 34. Mann-Whitney Test for Influence of Knowledge Sharing as Contingency on Individual Learning¹⁷

2. Team Level of Analysis

In this section, I explore the influence of knowledge sharing on team performance and team learning, in turn. Among the 16 experimental sessions, eight sessions require teams to play ELICIT with the support of knowledge sharing, and eight sessions require team to play ELICIT without the support of knowledge sharing.

a. Team Performance

Hypothesis 4 predicts that knowledge sharing improves team performance. As operationalized in the experimentation, the hypothesis suggests that teams playing the counterterrorism puzzlesolving game with the benefit of knowledge sharing should outperform teams undertaking the same complex, interdependent task without benefit of knowledge sharing. To test this prediction, I compare mean team performance under both conditions (see Table 35) based on the data collected during experimentation.

The team performance data parallel the results found within the individual performance data. Teams operating with knowledge sharing complete the task *more*

¹⁷ The Kolmogorov-Smirnov Z test, often used to compare means of observations of small sample sizes (i.e., $N \leq 25$) produces similar results.

slowly than their counterparts operating without knowledge sharing. On average, teams with the support of knowledge sharing complete the task at 0.350 (out of 1.0) on the dimensionless time scale, or approximately 42.2 minutes after each game begins. (Recall that for both dependent variables, the value 1.0 represents best possible performance while the value 0.0 represents worst possible performance.) On average, teams without the support of knowledge sharing, however, complete the task at 0.386 (out of 1.0) on the dimensionless time scale, or approximately 39.9 minutes after the game begins. Thus teams operating *with* the support of knowledge sharing complete the task, on average, 1.5 minutes *more slowly* than their counterparts. This initial comparison is contrary to the stated hypothesis, but the difference is negligible.

The influence of knowledge sharing on accuracy, however, is asymmetric. Teams operating with the support of knowledge sharing provide more accurate assessments of the impending terrorist attack, on average, than their counterparts operating without the support of knowledge sharing. On average, the accuracy is $0.678 - 0.508 = 0.17$ (out of 1.0) higher when the teams work *with* the support of knowledge sharing. This initial comparison is consistent with the hypothesis as stated.

		Knowledge Sharing	
		Not supported	Supported
Team Performance	Time		
	Mean	0.386	0.350
	Median	0.355	0.349
	Standard Deviation	0.061	0.167
	Accuracy		
	Mean	0.508	0.678
	Median	0.516	0.691
	Standard Deviation	0.166	0.142
	N	8	8

Table 35. Effect of Knowledge Sharing as Contingency on Team Performance

An error bar chart representing 95% confidence intervals around the means of the two dependent variables (see Figure 16) is somewhat promising for *Hypothesis 4*. As discussed above, the relationship with respect to team performance on the dimension time (in blue/solid) trends contrary to the prediction but is inconclusive.

For accuracy (in green/dashed), however, the relationship of mean performance between teams operating with or without the support of knowledge sharing is consistent with the predicted direction.

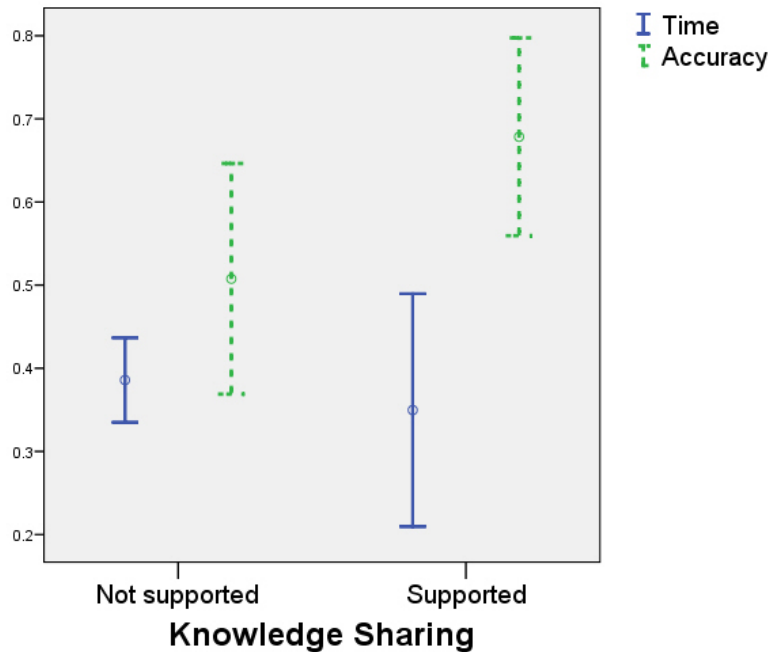


Figure 16. 95% Confidence Intervals around Dependent Variable Means – Effect of Knowledge Sharing as Contingency on Team Performance

Tests for normality indicate that the team performance data are normally distributed when teams are supported with knowledge sharing. However, the team performance data are not normally distributed for time when teams are not supported with knowledge sharing. Specifically, the Kolmogorov-Smirnov test for normality (Lilliefors 1967) suggests that the time data are normally distributed when knowledge sharing is supported ($D(8) = 0.136, p > 0.10$), but time data are not normally distributed when knowledge sharing is not supported ($D(8) = 0.310, p < 0.05$). The accuracy data are normally distributed under both conditions (i.e., supported with knowledge sharing – $D(8) = 0.205, p > 0.10$; not supported with knowledge sharing – $D(8) = 0.154, p > 0.10$). While the team performance data are heterogeneously variant ($F(1,14) = 4.154, p > 0.05$)

for time, team performance data for accuracy are homogeneously variant ($F(1,14) = 0.001, p > 0.10$). Non-parametric methods are most appropriate for the analysis.

The Mann-Whitney U test suggests that differences in team performance for time are not statistically significant and only a small effect is noted ($U = 27.0, p$ (one-tailed) $> 0.10, r = -0.13$). However, the differences in team performance for accuracy are not only statistically significant, but a medium effect size is noted ($U = 15.0, p$ (one-tailed) $< 0.05, r = -0.44$). *Hypothesis 4* is partially supported – i.e., at the team level, teams supported with knowledge produce more accurate responses to complex, interdependent tasks than teams that are not supported with knowledge sharing. Moreover, teams supported with knowledge sharing produce these more accurate results, completing the task at about the same time as teams *not* supported by knowledge sharing. Table 36 summarizes the results.

	Time	Accuracy
Mann-Whitney U	27.0	15.0
Wilcoxon W	63.0	51.0
Z	-.525	-1.785
Asymp. Sig. (2-tailed)	.600	0.74
Exact Sig. [2*(1-tailed Sig.)]	.645	.083
Effect Size (r)	-0.13	-0.44

Table 36. Mann-Whitney Test for Influence of Knowledge Sharing as Contingency on Team Performance

b. Team Learning

Hypothesis 5 predicts that when teams undertake complex and interdependent tasks, teams that are supported with knowledge sharing will learn more quickly than teams that are not supported with knowledge sharing. As operationalized within the research design, this hypothesis translates into an expectation that teams supported with knowledge sharing learn more quickly than teams not supported with knowledge sharing while playing the ELICIT game. To test this hypothesis, I compare team learning mean when teams are supported with knowledge against the team learning

mean when teams are not supported by knowledge sharing (see Table 37). Four observations are available under each condition.

A cursory examination of the data suggests that teams supported with knowledge sharing learn how to work more quickly than teams not supported with knowledge sharing. Specifically, teams supported with knowledge sharing, on average, improve their speed by 0.134, or about 8.7 minutes (out of approximately 60) per session. Teams not supported with knowledge sharing, on average, improve their speed by only 0.034, or about 2.2 minutes per experimental session. This relationship is consistent with the hypothesis as stated. In contrast, teams supported with knowledge sharing improve their accuracy less than teams not supported with knowledge sharing. Teams supported with knowledge sharing improve their accuracy, on average, only 0.143 per experimental session. Teams *not* supported with knowledge sharing improve their accuracy, on average, 0.183 per experimental session. The direction of the difference is contrary to the prediction, but the difference is also fairly small.

		Knowledge Sharing	
		Not supported	Supported
Team Learning	Time		
	<i>Mean</i>	.034	.134
	<i>Median</i>	.064	.189
	<i>Standard Deviation</i>	.098	.148
	Accuracy		
	<i>Mean</i>	.183	.143
	<i>Median</i>	.120	.130
	<i>Standard Deviation</i>	.202	.082
	<i>N</i>	4	4

Table 37. Effect of Knowledge Sharing as Contingency on Team Learning

An error bar chart (see Figure 17) depicts 95% confidence intervals around the means of the two measures of team learning. The figure suggests that while teams learn how to work more quickly when supported with knowledge sharing, this learning is more volatile than learning by teams without knowledge sharing (in blue/solid). The figure also suggests that teams supported with and without knowledge

sharing learn to work more accurately at about the same rate (in green/dashed). The error bar chart thus suggests that *Hypothesis 5* is not supported.

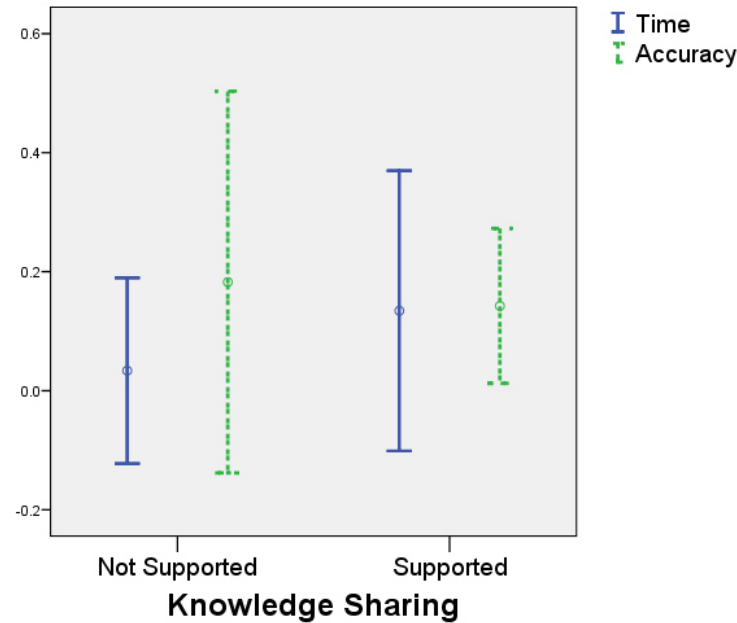


Figure 17. 95% Confidence Intervals around Dependent Variable Means – Influence of Knowledge Sharing as Contingency on Team Learning

The Shapiro-Wilk test suggests that the team learning data are normally distributed for both accuracy and time. Specifically, the Shapiro-Wilk test suggests that the team learning data for time are normally distributed when knowledge sharing is supported ($D(4) = 0.868, p > 0.10$) and when knowledge sharing is not supported ($D(4) = 0.810, p > 0.10$). The Shapiro-Wilk test suggests that the team learning data for accuracy are normally distributed when knowledge sharing is supported ($D(4) = 0.871, p > 0.10$) and not supported ($D(4) = 0.371, p > 0.10$). Levene's test also suggests that the team learning data are homogeneously variant for time ($F(1,6) = .620, p > 0.10$) and accuracy ($F(1,6) = 1.699, p > 0.10$). Parametric methods are appropriate for the analysis.

The t -test suggests that differences in team learning for the time measure are not statistically significant, although a medium effect is noted despite the small sample sizes ($t(6) = -1.13, p$ (one-tailed) $> 0.10, r = 0.42$). Further, differences in team

learning relative to the accuracy measure are not statistically significant, and only a small effect size is noted ($t(6) = 0.37$, p (one-tailed) > 0.10 , $r = 0.15$). *Hypothesis 5* is not supported – i.e., team learning does not appear to be influenced by the support of knowledge sharing for either measure. Given the small sample size ($N = 8$) and medium effect noted during experimentation for team learning relative to time, we should not necessarily reject this hypothesis out of hand. Further investigation could prove fruitful and illuminating, especially given the large body of extant literature that contends knowledge sharing is an important influence on collective learning (e.g., March 1991; Argote et al. 2003; Devadas Rao & Argote 2006). Table 38 summarizes the results.

	<i>t</i>	<i>df</i>	Sig. (2-tailed)	Effect size
Time	-1.133	6	.300	0.42
Accuracy	.368	6	.726	0.15

Table 38. Results of *t*-test for Effect of Knowledge Sharing as Contingency on Team Learning

C. DISCUSSION

In this section, I briefly recapitulate main effects from the experimentation relative to each of the dependent variable constructs, in turn. A short summary of the hypothesis testing is provided in Table 39 below.

1. Individual Performance

Both hypotheses regarding individual performance are supported. Specifically, individuals operating within Edge teams outperform counterparts operating within Hierarchy teams (*Hypothesis 1a*), working more quickly and more accurately than similar individuals assigned to Hierarchy teams. Moreover, individuals operating in teams supported by knowledge sharing outperform individuals operating in teams without knowledge sharing (*Hypothesis 4a*), working more quickly and more accurately than counterparts. Of the two manipulations, operating within an Edge information processing structure appears to produce the larger effect on individual performance.

The support for these hypotheses lend support to notions that when an individual performs complex tasks in which information inputs are arranged in a reciprocally interdependent manner, both information processing structure (i.e., centralization, formalization and vertical differentiation) and an ability to exchange knowledge with others will influence how accurately and how quickly the individual performs the task. As predicted, the structure of information flows within a team affects individual performance; moreover, an ability to send and receive actionable information with others affects performance. Specifically, structures emphasizing low centralization, low formalization and low vertical differentiation enable individuals to outperform similar persons operating in structures with high centralization, high formalization and high vertical differentiation. Further, providing individuals with opportunities to share and receive knowledge from others assists them to complete complex tasks more quickly and more accurately. Based on these findings, it could also prove useful to explore the interaction of structure and knowledge sharing against individual performance.

2. Individual Learning

Both hypotheses related to individual learning are partially supported. Specifically, individuals operating within Edge teams learn to how to complete their work more quickly than individuals operating within Hierarchy teams (*Hypothesis 3a*). Moreover, individuals operating within teams supported by knowledge sharing learn how to complete their work more quickly than individuals operating within teams not supported by knowledge sharing (*Hypothesis 5a*). Both effect sizes are small and influence is confined to learning how to complete tasks more quickly, not more accurately.

Although the individual learning hypotheses are only partially supported, the experimental results are still important for researchers focused on this topic and could potentially serve as motivators for subsequent research. Under either information processing structure (i.e., Edge, Hierarchy) or either knowledge sharing condition (i.e., Supported, Not Supported), individuals improve their accuracy. This finding suggests that when repeating relatively similar complex tasks in which information is distributed

in a manner that creates reciprocal interdependence among organizational agents, *individual improvements in accuracy are indifferent to manipulations of information processing structure or manipulations of knowledge sharing.*

However, *individual improvements in the speed of completing complex, interdependent tasks are influenced by both structure and knowledge sharing.* These results demonstrate support for a theoretical model in which the interaction of information processing structure and knowledge sharing is expected to influence individual learning, at least relative to how much time is required to complete a task. More specifically, the findings suggest that individuals assigned to team structures with low centralization, low formalization and low vertical differentiation *and* supported by knowledge sharing will learn how to produce their work more quickly than similar individuals assigned to alternate structure-knowledge sharing conditions. However, these interactions may influence elements of performance—such as improving the accuracy of one’s work or improving the timeliness of one’s work—differently.

3. Team Performance

The team performance hypotheses are partially supported, although manipulating information processing structures and knowledge sharing produces mixed results. As predicted by *Hypothesis 1*, Edge teams outperform Hierarchy teams at complex tasks with reciprocal interdependence of the information inputs – but only in terms of identifying details of the terrorist attack more quickly. Observed accuracy is relatively equal for both Edge and Hierarchy teams. This finding suggests that team structure may influence some dimensions of performance (e.g., time required to complete a task) more significantly than other dimensions of performance (e.g., accuracy of completed work). In contradistinction, teams supported *and* not supported by knowledge sharing complete the task at relatively equal rates (*Hypothesis 4*). Further, teams supported by knowledge sharing provide more accurate identifications of the terrorist attack.

Put simply, structure influences the speed at which a teams complete complex, interdependent tasks; knowledge sharing influences accuracy of the completed work. These findings lend support to a theoretical model in which the *interaction* of information

processing structure and knowledge sharing may influence team performance differently. Based on these results, for example, we might expect for Edge teams supported with knowledge sharing to produce the highest level of performance compared to all alternatives. Similarly, we might expect Hierarchy teams *not* supported with knowledge sharing to produce the lowest level of performance.

4. Team Performance under Structural Transformation

One of the most striking and exciting results of the experimentation stems from the transformation of team information processing structures (*Hypothesis 2*). Comparative analysis of the team transformed from Edge to Hierarchy, and vice versa, suggests that transforming a team's structure results in asymmetric performance. Specifically, when Team C was transformed from Edge to Hierarchy, its performance degraded considerably – both time and accuracy measures were negatively affected. When Team B transformed from Hierarchy to Edge, however, the team maintained its previous level of accuracy, while completing its work much more quickly than the previous experimental session. Team B thus improved how quickly it completed the task with no degradation in accuracy, despite a significant structural transformation. Team C, undergoing the converse structural transformation, exhibited degradation on both dimensions of performance.

The experimental data suggest that the influence of structural transformation on team performance *is dependent upon the direction of the transformation*. Transitioning from a more mechanistic information processing structure (i.e., high centralization, high formalization and high vertical differentiation) to a more organic information processing structure (i.e., low centralization, low formalization and low vertical differentiation) considerably enhances performance. Transitioning from a more organic information processing structure (i.e., low centralization, low formalization, and low vertical differentiation) to a more mechanistic information processing structure (i.e., high centralization, high formalization, and high vertical differentiation) considerably degrades performance. Although more research is needed, the data suggest that it may be possible use laboratory experimentation to approximate, at least in part, the performance

costs associated with structure-task misfit. Moreover, the data suggest that when a team usually structured as a Hierarchal information processing system encounters a task for which “Edge-like” organizing may be more suitable, restructuring a team’s information flows, perhaps via a technological intervention such as a collaborative tool for exchanging actionable information, may be a useful means for quickening the completion of work while maintaining the existing set of team members while producing results of similar or better accuracy.

This finding has particular implications for situations in which effective action requires faster response times over standard protocols (e.g., crisis/emergency management, disaster response, others). It seems plausible that “Edge-like” organizing within teams (i.e., low centralization, low formalization, and low vertical differentiation) represents some type of minimal structure that facilitates sufficient team-level sensemaking (Weick et al. 2005) needed to perform complex tasks, and to do so quickly. However, “Edge-like” organizing does not reduce structure so significantly that organizational sensemaking also collapses (e.g., Weick 1993a).

At the micro-organizational level, teams acculturated to Hierarchy structures can maintain existing information flows when transformed into Edge structures, while allowing new information flows to emerge through the transition. For Edge teams that are transformed to Hierarchy structures, however, existing information flows may require radical readjustment and thus likely contribute to degradations in performance as the team reorganizes its information flows in accordance with the more restrictive Hierarchal information processing structure. Although further investigation is needed, it seems plausible that the transition from Hierarchy to Edge organizing within the experimentation instantiates the combination of “structuring mechanisms, ... constrained improvisation, and cognition management methods that ... lead to exceptional organizational reliability under volatile environmental conditions” (Bigley & Roberts 2001, p. 1282) described by Bigley and Roberts (2001) in an inductive ethnography of the incident command management system, which is used ubiquitously within the initial response stages of emergency and crisis management.

5. Team Learning

Finally, I tested both hypotheses related to team learning. *Hypothesis 3*, which predicts that Edge teams learn more quickly than Hierarchy teams, was not supported. *Hypothesis 5*, which predicts that teams supported with knowledge sharing learn more quickly than teams not supported with knowledge sharing, was also not supported. While the experimentation did not support the hypotheses as stated, the finding that team learning is indifferent—at least in the statistical sense—to manipulation of a team's information processing structure and its ability to share knowledge are important. The findings suggest that there is no one best way to facilitate team learning via manipulations to structure or knowledge sharing when teams undertake complex, reciprocally interdependent tasks.

However, consistent with Dar-el (2000) and Devadas Rao and Argote (2006), team learning is not negligible in the absolute sense; practice (i.e., task repetition) assists teams to improve their accuracy and improve the speed at which tasks are completed. Further, while strict statistical interpretation would suggest that team learning is largely indifferent to manipulations of structure and knowledge sharing, the small sample size and medium effect size for *time* suggest that knowledge sharing may indeed enable teams to learn how to complete their work *more quickly*. As such, the *combined* influence of information processing structure and knowledge sharing on team learning should not be dismissed out of hand, and further work in this area with a more complex theoretical framework would likely prove illuminating.

A summary of the hypothesis testing is provided in Table 39 below.

	Time (sig.) ¹⁸	Effect size	Accuracy (sig.) ¹⁸	Effect size	Test	Assessment ¹⁹
Individual Performance						
1a. Structure: Edge outperforms Hierarchy	$p < 0.001$	Medium	$p = 0.053$	Small	Mann-Whitney U	Supported
4a. Contingency: Supported outperforms not supported	$p < 0.001$	Small	$p < 0.01$	Small	Mann-Whitney U	Supported
Individual Learning						
3a. Structure: Edge learns more quickly than Hierarchy	$p < 0.05$	Small	n.s.	Small	Mann-Whitney U	Partially supported
5a. Contingency: Supported learns more quickly than not supported	$p < 0.05$	Small	n.s.	n.s.	Mann-Whitney U	Partially supported
Team Performance						
1. Structure: Edge outperforms Hierarchy	$p = 0.053$	Medium	n.s.	Small	ANOVA	Partially supported
4. Contingency: Supported outperforms not supported	n.s.	Small	$p < 0.05$	Medium	Mann-Whitney U	Partially supported
Team Performance under Structural Transformation						

¹⁸ In this table, all significance values are one-tailed as the hypotheses under test posit directional relationships.

¹⁹ Since two tests were conducted in addition to the multivariate analyses presented in the previous chapter, the Bonferroni correction would suggest dividing the desired α value by two (Field 2005). Within Table 39, this correction would result in rejecting the hypotheses for $p > 0.025$.

	Time (sig.) ¹⁸	Effect size	Accuracy (sig.) ¹⁸	Effect size	Test	Assessment ¹⁹
2. Structure: Structural transformation influences performance	<ul style="list-style-type: none"> Transforming to Edge improves performance Transforming to Hierarchy degrades performance 	n/a	<ul style="list-style-type: none"> Transforming to Edge results in same performance Transforming to Hierarchy degrades performance 	n/a	Comparative analysis of one observation under each transformation condition	Intriguing results that suggest further investigation is needed
Team Learning						
3. Structure: Edge learns more quickly than Hierarchy	n.s.	n.s.	n.s.	Small	<i>t</i> -test	Despite small sample size, the effect size for accuracy suggests that further investigation could be fruitful
5. Contingency: Supported learns more quickly than not supported	n.s.	Medium	n.s.	Small	<i>t</i> -test	Despite small sample size, the effect size for time suggests further investigation could be fruitful

Table 39. Summary of Hypothesis Testing

D. SUMMARY

In this chapter, I tested the main effects of manipulating information processing structure and knowledge sharing on the dependent variable constructs of individual performance, individual learning, team performance and team learning using the measures of time and accuracy outlined in the research design. In so doing, I tested each of the nine hypotheses motivated in the literature review provided in Chapter II. The hypotheses received mixed levels of support based on the dependent variable constructs, but the results are nonetheless exciting and promising. In particular, the independent variables of information processing structure and knowledge sharing result in discernible influences on individual performance, individual learning, and team performance. Moreover, the *interactions* of these variables, as hypothesized by the theoretical model,

appear to be particularly important for explaining variance within the dependent variable constructs. In the next chapter, I explore the interaction effects of the manipulations, consistent with a theoretical model that suggests that knowledge sharing moderates the relationship between information processing structure and performance.

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VI. INTERACTION EFFECTS

In the previous chapter, I tested my motivated hypotheses. At the individual level of analysis, I found support for predictions that information processing structures and knowledge sharing as contingency influence individual performance and individual learning. At the team level of analysis, I found support for predictions that information processing structures and knowledge sharing as contingency influence team performance. However, I did not find support for predictions that varying information processing structures or varying knowledge sharing influences team learning. I also found an intriguing outcome about the influence of structural transformation on teams. Specifically, the experimental results suggest that *the direction* of structural transformation influences teams asymmetrically. Transforming from Edge to Hierarchy, for example, significantly degrades performance. Transforming from Hierarchy to Edge, however, significantly enhances performance, at least with respect to completing the complex, interdependent task more quickly.

The theoretical model undergirding my research suggests that knowledge sharing serves as a moderating influence between information processing structure and performance. As a result, I expect that combinations of manipulating team information processing structures and manipulating the ability to share knowledge may influence performance differently. In this chapter, I explore these interaction effects. Various statistical tests associated with individual performance, individual learning, and team performance suggest that interaction effects between information processing structure and knowledge sharing may be most critical within these dependent constructs (see Table 21 in the summary of Chapter IV). For examining interaction effects, I thus concentrate on individual performance, individual learning, and team performance, in turn. The reader most interested in the results of the analyses may wish to skip to the discussion section toward the end of the chapter.

A. RANK TRANSFORMATION

Rank transformation is well-established for exploring main effects within experimental designs resulting in non-parametric dependent variable data (Akritas 1990; Akritas & Arnold 1994; Conover 1999). However, testing for interaction effects using rank transforms provides mixed results (Pavur & Nath 1986; Sawilowsky et al. 1989; Sawilowsky 1990; Thompson 1991; Conover 1999; Gao & Alvo 2005). To explore the influence of interactions among independent variables, Conover (1999) suggests experimenters should compare results of parametric and non-parametric analyses; if the results are sufficiently similar, the experimenter can accept the parametric (e.g., ANOVA) results as valid. Alternatively, Marden and Muyot (1995) recommend orthogonal contrasts as a means for exploring interaction effects with non-parametric methods, allowing use of Mann-Whitney *U* and like tests when the acceptable α values are adjusted using Bonferroni or Sidak corrections. Orthogonal contrasts using non-parametric data do not provide the magnitude of interaction effects compared to the magnitude of main effects *per se*. However, when applied to experimentation with multiple independent variables, such contrasts do indicate whether specific combinations of experimental conditions are statistically different from other combinations of experimental conditions.

B. INDIVIDUAL PERFORMANCE

In this section, I discuss interaction effects of information processing structure and knowledge sharing on individual performance.

1. Example

Based on the experimental data, the *interaction* of information processing structure and knowledge sharing appears to significantly influence individual performance. For example, Table 22 illustrates that individuals assigned to Edge structures complete their work *more quickly* than individuals assigned to Hierarchy structures, consistent with *Hypothesis 1a*. However, Table 31 indicates that individuals supported by knowledge sharing complete the task *more slowly* than their counterparts,

contrary to *Hypothesis 4a*. These results intimate that the *interaction* of structure and contingency may influence how quickly individuals complete their work and thus deserves further investigation through comparing individual performance as observed under the four structure-contingency combinations. Table 40 assists with these comparisons by summarizing observed individual performance under each experimental condition.

2. Accuracy

As Table 40 illustrates, accuracy is highest when individuals are assigned to Edge information processing structures supported by knowledge sharing (E-K), but accuracy is also quite high when individuals assigned to Hierarchy teams supported by knowledge sharing (H-K). Individuals assigned to Edge information processing structures average accuracy scores of 0.614 when *not supported* by knowledge sharing (E-nK); individuals operating with Edge information processing structures average accuracy scores of 0.749 when *supported* by knowledge sharing (E-K). (Recall that for the performance dimensions time and accuracy, the value 1.0 represents best possible performance while the value 0.0 represents worst possible performance.) For individuals assigned to Edge groups, knowledge sharing, on average, improves accuracy by $0.749 - 0.614 = 0.135$ (out of 1.0). Similarly, individuals assigned to Hierarchy teams *without* knowledge sharing (H-nK) average accuracy scores of 0.597, while individuals assigned to Hierarchy teams *with* knowledge sharing (H-K) average accuracy scores of 0.694. For individuals within Hierarchy teams, then, support of knowledge sharing improves accuracy by $0.694 - 0.597 = 0.097$. On average, knowledge sharing improves accuracy, regardless of information processing structure. However, knowledge sharing improves individual accuracy *most* when assigned to Edge information processing structures.

3. Time

For time, however, the effect is bi-directional. Individuals assigned to Edge teams *not* supported by knowledge sharing (E-nK) complete the task, on average, with a time score of 0.453, while individuals assigned to Edge teams supported by knowledge

sharing (E-K) complete the task, on average, with a time score of 0.474. Working within an Edge team supported by knowledge sharing (E-K) thus assists individuals to provide their identifications of the terrorist attack about $0.474 - 0.453 = 0.021$, or 1.36 minutes, *faster* than individuals in Edge teams not supported with knowledge sharing (E-nK). The opposite influence, however, is noted for individuals assigned to Hierarchy teams. Specifically, individuals assigned to Hierarchy teams supported with knowledge sharing (H-K) complete the task with a time score of 0.252 (recall that 0.0 reflects worst possible performance and 1.0 reflects best possible performance), while individuals assigned to Hierarchy teams without knowledge sharing (H-nK) complete the task with a time score of 0.472. During the experimentation, individuals working with Hierarchy teams supported with knowledge sharing complete the task $0.472 - 0.252 = 0.220$, or nearly 14.3 minutes, *slower* than their counterparts in Hierarchy teams *not* supported with knowledge sharing.

Put simply, knowledge sharing improves accuracy regardless of type of information processing structure to which a subject is assigned; moreover, accuracy is enhanced most when individuals are assigned to Edge information processing structures moderated by knowledge sharing. Further, knowledge sharing assists individuals assigned to Edge structures to complete the task more quickly, while knowledge sharing *slows* completion of the task for individuals assigned to Hierarchy information processing structures. Relative to individual performance, the interaction of knowledge sharing and information processing structure produces a uni-directional effect for accuracy (improves both information processing structures) and bi-directional effect for time (improves Edge slightly, degrades Hierarchy considerably).

		Knowledge Sharing					
		<i>Supported</i>			<i>Not Supported</i>		
	Accuracy	μ	σ	N	M	σ	N
Information Processing Structure	<i>Edge</i>	0.749	0.272	66	0.614	0.350	46
	<i>Hierarchy</i>	0.694	0.255	62	0.597	0.248	36
	Time	μ	σ	N	μ	σ	N
Information Processing Structure	<i>Edge</i>	0.474	0.192	66	0.453	0.166	46
	<i>Hierarchy</i>	0.252	0.194	62	0.472	0.097	36

Table 40. Comparison of Information Processing Structure Moderated by Knowledge Sharing as Contingency – Individual Performance

4. Contrasts for Individual Performance

This cursory examination of the data, as summarized in Table 40, suggests the following contrasts for statistical analysis. Results of the analyses are reported in parentheses based on Mann-Whitney U tests for a non-parametric comparison of means. Given the contrasts below, the Bonferroni α correction would suggest rejecting the

statements if $p > \frac{0.05}{5} = 0.01$ (accuracy) and $p > \frac{0.05}{4} = 0.0125$ (time)²⁰:

- E-K vs. E-nK: Individuals assigned to Edge teams supported by knowledge sharing produce more accurate work than individuals assigned to Edge teams not supported by knowledge sharing ($U = 1323.0$, p (one-tailed) = 0.02, $r = -0.19$, small effect, $N = 112$)
- H-K vs. H-nK: Individuals assigned to Hierarchy teams supported by knowledge sharing produce more accurate work than individuals assigned to Hierarchy teams not supported by knowledge sharing ($U = 874.5$, p (one-tailed) = 0.036, $r = -0.18$, small effect, $N = 98$)
- E-K vs. H-K: Individuals assigned to Edge teams supported by knowledge sharing produce more accurate work than individuals assigned to Hierarchy

²⁰ The Bonferroni corrections given here include an adjustment of the α values due to the planned contrasts associated with the main effects – i.e., Edge vs. Hierarchy and Knowledge Sharing Supported vs. Knowledge Sharing Not Supported – reported in Chapter V.

teams supported by knowledge sharing ($U = 1709.5$, p (one-tailed) = 0.049, $r = -0.15$, small effect, $N = 128$)

- H-K vs. all: Individuals assigned to Hierarchy teams supported by knowledge sharing complete their work more slowly than individuals assigned to all other combinations of information processing structure and knowledge sharing (compared to Edge with knowledge sharing *only*: $U = 855.0$, p (one-tailed) < 0.001, $r = -0.50$, large effect, $N = 128$, compared to all other groups: $U = 1717.0$, p (one-tailed) < 0.001, $r = -0.49$, medium effect, $N = 210$)

With the Bonferroni correction, only the final contrast is statistically significant. Specifically, individuals assigned to Hierarchy teams supported by knowledge sharing (H-K) complete their work more slowly than individuals operating under all other conditions. Moreover, the effect size is quite sizable.

5. Indifference Curves for Individual Performance

Those interested in design of team information processing structures and knowledge sharing systems might find it helpful to envision the two dimensions of performance on a grid, with time on the x -axis and accuracy on the y -axis. Such a grid is illustrated in Figure 18, along with four unique $y = -x + b_i$ indifference curves with b_i as unspecified constants.²¹ The indifference curves represent levels of relative performance (i.e., closest to the origin = worst performance, farthest from the origin = best performance) in which the designer has equally weighted time and accuracy (e.g., an 0.10 improvement in speed is equal to an 0.10 improvement in accuracy). Any point along an indifference curve would be considered as providing comparable performance. Consistent with notation used through this work, In Figure 18, E-K refers to the mean values for individual performance relative to time and accuracy for individuals assigned

²¹ The indifference curves are provided for illustrative purposes and to facilitate discussion. If stakeholder preferences for time and accuracy could be mapped using human subjects designing ‘real-world’ teams in field settings, the indifference curves may not appear linear in shape and may instead take alternate forms, such as functions approximated by an inverse power law (Jones 2007). Fundamentally, the discussion herein relates to creating a univariate measure for comparing performance. However, creation of such a univariate measure is left to future work.

to Edge teams with knowledge sharing, E-nK refers to Edge without knowledge sharing, H-K refers to Hierarchy with knowledge sharing, and H-nK refers to Hierarchy without knowledge sharing.

In such a performance space, the individuals assigned to Hierarchy teams with knowledge sharing (H-K) *underperform* all others, while the individuals assigned to Edge teams with knowledge sharing (E-K) *outperform* all others. When knowledge sharing is not supported, the experimental observations suggest that the Edge (E-nK) and Hierarchy (H-nK) fall along nearly similar indifference curves – i.e., they are interchangeable in terms of observed performance.

The indifference curves described here are useful for discussing and evaluating organizational performance, but are simplistic in nature as they assume that stakeholders value time and accuracy equally. The indifference curves thus provide an example of how an organizational designer might evaluate the observed performance of combinations of information processing structure and knowledge sharing combinations *relative to each other and stakeholder values*. The indifference curves in Figure 18 below serve only as illustration and do not reflect the full range of performance outcomes in which an organizational designer and associated stakeholders might be interested. Nonetheless, the curves indicate that individuals assigned to Edge teams supported with knowledge sharing (E-K) clearly outperform all others when stakeholders value *timeliness of response* and *accuracy of response* equally.. Further, individuals assigned to Hierarchy teams supported with knowledge sharing (H-K) underperform all others when stakeholders value *timeliness of response* and *accuracy of response* equally.

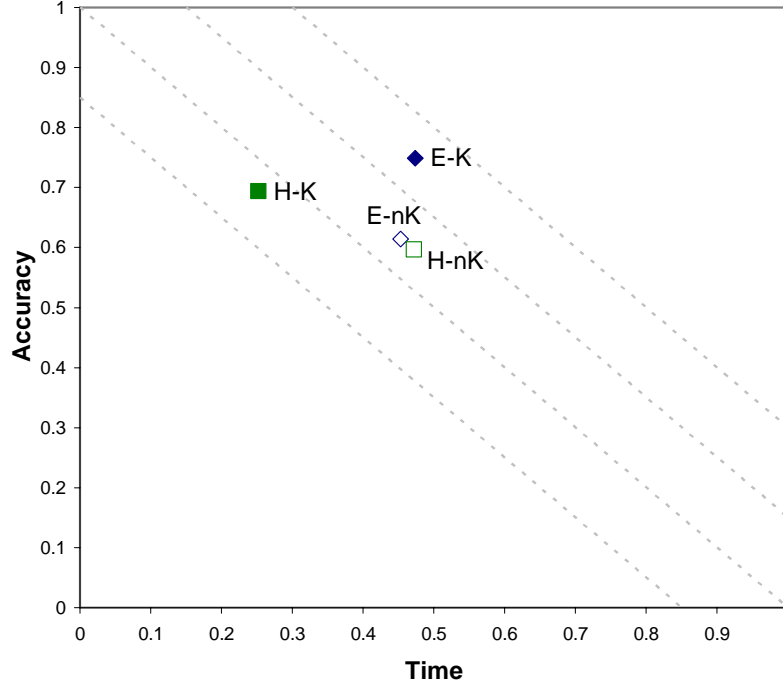


Figure 18. Indifference Curves Reflecting Interaction of Information Processing Structure and Knowledge Sharing as Contingency on Individual Performance

6. Sensitivity Analysis of Indifference Curves for Individual Performance

Figure 18 reflects indifference curves reflecting when stakeholders weight *time to complete task* and *accuracy of provided product* equally. However, the results appear robust across a number of valuation strategies (such as *time* weighted by 0.2 and *accuracy* weighted by 0.8, or *time* weighted by 0.7 and *accuracy* weighted by 0.3). It is thus useful to determine the sensitivity of the results to variation in stakeholders' weighting strategies.

Again using a simple linear equation, we can think of an indifference curve involving both *time* and *accuracy* as

$$\beta = \alpha X_{s-c} + \gamma Y_{s-c} \quad \text{Eq. (4)}$$

In this equation, X_{s-c} represents mean individual *time* to complete the task when assigned to a particular structure-contingency combination (e.g., $X_{E-K} = 0.474$, see Table

40), and α is the stakeholders' weight for *timeliness of response*. Similarly, Y_{s-c} represents the mean individual *accuracy* of the provided product when assigned to a particular structure-contingency combination (e.g., $Y_{H-nK} = 0.597$, see Table 40), and γ is the stakeholders' weight for *accuracy of response*. If we vary α and γ according to the stakeholders' valuation strategy and such that their sum is equal to one, we can determine which structure-contingency combination is more optimal for various values of α and γ . More specifically, for any given value α , γ , X_{s-c} , and Y_{s-c} , we can determine which of the four structure-contingency combinations provides the maximal β . This maximal β , in turn, represents the more optimal performance *given a specific stakeholders' valuation strategy for weighting time and accuracy*. We can then rank each of the structure-contingency combinations relative to the stakeholders' weightings. The rankings provide a rudimentary sensitivity analysis for the indifference curves described in the previous section.

An illustrative sensitivity analysis is summarized in Table 41, with Edge structures listed in **bold** and Hierarchy structures listed in *italics*. Teams supported by knowledge sharing are highlighted in yellow (light grey), while teams *not* supported by knowledge sharing are not highlighted. We notice, for example, that regardless of the multiples applied to either *time* or *accuracy*, individuals within the Edge team supported with knowledge sharing (E-K) outperform similar individuals subject to all other structure-contingency combinations (i.e., Rank 1). This result suggests that individual performance within Edge teams supported by knowledge sharing (E-K) is consistent across significant variation in the weights that stakeholders apply to either *time* or *accuracy*. Notice, however, that the ranks of the other structure-contingency conditions (i.e., E-nK, H-K, H-nK) are not nearly as stable; the ranks vary relative to how stakeholders weight *time* and *accuracy*.

Stakeholder Values		Rank			
<i>Multiple of Time</i>	<i>Multiple of Accuracy</i>	<i>Best</i>			<i>Worst</i>
α	γ	1	2	3	4
0.1	0.9	E-K	H-K	E-nK*	H-nK*
0.2	0.8	E-K	H-K	E-nK*	H-nK*
0.3	0.7	E-K	E-nK*	H-K	H-nK*
0.4	0.6	E-K	E-nK*	H-nK*	H-K
0.5	0.5	E-K	H-nK*	E-nK*	H-K
0.6	0.4	E-K	H-nK*	E-nK*	H-K
0.7	0.3	E-K	H-nK*	E-nK*	H-K
0.8	0.2	E-K	H-nK*	E-nK*	H-K
0.9	0.1	E-K	H-nK*	E-nK*	H-K

* As Figure 18 illustrates, the H-nK and E-nK structure-contingency combinations provide nearly equal results and thus distinctions between their relative rankings should be interpreted with some caution.

Table 41. Sensitivity of Individual Performance to Varying Stakeholder Values for Time and Accuracy

For example, if stakeholders weight accuracy *significantly more* than time (e.g., $\alpha = 0.1$ and $\gamma = 0.9$), individuals in Hierarchy teams supported by knowledge sharing (H-K) outperform similar individuals in the remaining two structure-contingency combinations (i.e., E-nK, H-nK). However, as stakeholders place less emphasis on *accuracy* and more emphasis on *time* (e.g., $\alpha = 0.5$ and $\gamma = 0.5$), individuals within Edge structures *not* supported by knowledge sharing (E-nK) rank second. Finally, as stakeholders weight time *significantly more* than accuracy (e.g., $\alpha = 0.9$ and $\gamma = 0.1$), individuals in Hierarchy teams not supported by knowledge sharing (H-nK) rank second compared to the remaining two structure-contingency combinations (i.e., E-nK, H-K).

An important caution is necessary when interpreting Table 41. Specifically, the numeric values underlying the rankings suggest that Edge structures not supported by knowledge sharing (E-nK) and Hierarchy structures not supported by knowledge sharing (H-nK) wield similar influences on individual performance. This near-equivalence of the two structure-contingency combinations (i.e., E-nK, H-nK) is also clear through visual inspection of Figure 18. Numerically, the two structure-contingency combinations (i.e., E-nK, H-nK) are *nearly equal*, separated by -0.015 to 0.015 (out of a possible difference of -1.0 to 1.0) when the relative weights of α and γ are applied. Therefore, despite the

rankings provided here, any assessment that individuals within Edge structures not supported by knowledge sharing (E-nK) outperform individuals working within Hierarchy structures not supported by knowledge sharing (H-nK) requires further investigation.

C. INDIVIDUAL LEARNING

In this section, I discuss interaction effects of information processing structure and knowledge sharing on individual learning.

1. Time

Like individual performance, the experimental data suggest that interaction of information processing structures and knowledge sharing influence individual learning in unique ways. A summary of the individual learning data is provided in Table 42, and the results are intriguing. Relative to time, the Edge structure with knowledge sharing appears to improve individual learning significantly ($\mu = .206$), while the three other combinations of structure and knowledge sharing are nearly similar and indeed, appear nearly negligible in magnitude ($.011 \leq \mu \leq .046$). The Edge information processing structure, as moderated by knowledge sharing, seems most suited to assisting individuals to learn how to complete tasks more quickly.

2. Accuracy

Relative to accuracy, however, the results are more uneven. On average, the Edge structure *not* supported by knowledge sharing provides the most suitable structure-contingency combination for learning how to produce more accurate work ($\mu = .284$) at the individual level of analysis. In contrast, the Hierarchy structure *not* supported by knowledge sharing provides the least suitable structure-contingency combination for learning how to produce more accurate work at the individual level of analysis ($\mu = .014$). However, *both* information processing structures, when supported by knowledge sharing, *equally* assist individuals with learning how to produce more accurate work ($.175 \leq \mu \leq .176$).

		Knowledge Sharing					
		<i>Supported – Supported</i>			<i>Not Supported – Not supported</i>		
		μ	σ	N	μ	σ	N
Information Processing Structure	<i>Edge – Edge</i>	.176	.394	18	.284	.333	14
	<i>Hierarchy - Hierarchy</i>	.175	.289	19	.014	.348	11
	Time	μ	σ	N	μ	σ	N
Information Processing Structure	<i>Edge – Edge</i>	.206	.221	18	.020	.177	14
	<i>Hierarchy - Hierarchy</i>	.011	.312	19	.046	.103	11

Table 42. Comparison of Information Processing Structure Moderated by Knowledge Sharing as Contingency – Individual Learning

3. Contrasts for Individual Learning

This cursory review of the experimental data suggests that three contrasts might prove particularly enlightening for exploring the interaction of Edge information processing structure and knowledge sharing as it influences individual learning. Results of the analyses are reported in parentheses based on Kolmogorov-Smirnov Z test²² for non-parametric comparison of means. Given the contrasts below, the Bonferroni α

correction would suggest rejecting the statements if $p > \frac{0.05}{4} = 0.0125$ (accuracy) and

$p > \frac{0.05}{3} = 0.0167$ (time):

- E-nK vs. all: Relative to accuracy, individual learning within Edge teams *not* moderated by knowledge sharing is higher than individual learning subject to all other combinations of information processing structure and knowledge sharing ($Z = .637, p$ (one-tailed) $> 0.10, r = 0.08$, n.s., $N = 62$)
- H-nK vs. all: Relative to accuracy, individual learning within Hierarchy teams *not* moderated by knowledge sharing is lower than individual learning

²² For comparison of means when data is non-parametric, the Kolmogorov-Smirnov Z test is preferred over the Mann-Whitney U test when sample sizes are small (Field 2005).

subject to all other combinations of information processing structure and knowledge sharing ($Z = 1.346$, p (*one-tailed*) = 0.027, $r = 0.17$, small effect, $N = 62$)

- E-K vs. all: Relative to time, individual learning within Edge teams moderated by knowledge sharing is higher than individual learning subject to all other combinations of information processing structure and knowledge sharing ($Z = 1.922$, p (*one-tailed*) < 0.001, $r = 0.24$, small effect, $N = 62$)

With the Bonferroni correction, the experimental data suggest that only the first planned contrast provides significant results. Specifically, Edge teams moderated by knowledge sharing influence individual learning with respect to time – i.e., assignment to an Edge team moderated by knowledge sharing helps individuals learn how to complete complex, interdependent tasks more quickly. Assignment to a Hierarchy team *not* moderated by knowledge sharing may limit an individual’s ability to produce more accurate work, but this result is not statistically significant.

4. Indifference Curves for Individual Learning

Figure 19 illustrates the mean values for individual learning graphically, using the same coding schema as Figure 18 (i.e., E-K represents Edge with knowledge sharing, H-nK represents Hierarchy without knowledge sharing, and so forth). The graph reflects that individual improvement in time is highest for individuals assigned to Edge teams with knowledge sharing (E-K). Individual improvement in time and accuracy is least for individuals assigned to Hierarchy teams without support of knowledge sharing (H-nK). Figure 19 also includes indifference curves in which improvement in time (i.e., individual learning, shown on the x -axis) is equally weighted against improvement in accuracy (i.e., individual learning, shown on the y -axis). For individual learning, the indifference curves clearly suggest that the Edge information processing structure is the superior form, and moreover, that the Edge information processing structure moderated by knowledge sharing (E-K) supports individual learning *most*.

Reflecting upon the indifference curves, the third “best” structure-contingency combination for individual learning is Hierarchy moderated by knowledge sharing (H-K). Individual learning within the combination of these two experimental conditions (i.e., Hierarchy supported by knowledge sharing) is lower than individual learning under both Edge conditions (i.e., E-K and E-nK). However, individual learning when Hierarchy information processing structure and knowledge sharing interact (H-K) is *higher* than when the Hierarchy structure is not supported with knowledge sharing (H-nK).

These comparisons support a number of conclusions that could serve as motivators for future work. For example, manipulating a team’s information processing structure does appear to influence individual learning in important ways. Chiefly, structures with low centralization, low formalization, and low vertical differentiation support individual learning to a greater extent than structures with properties of high centralization, high formalization, and high vertical differentiation. Moreover, when knowledge sharing is supported, individual learning improves. The experimental data thus support a theoretical model in which the *interaction* of structure and contingency influence individual learning.

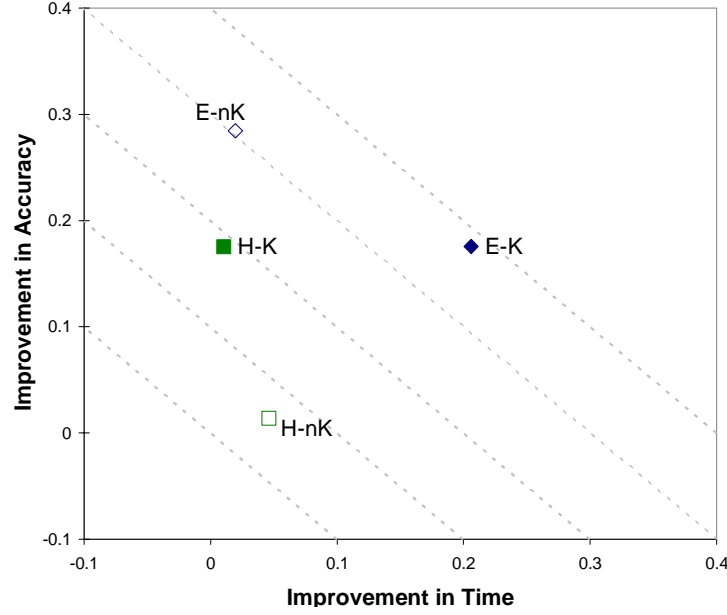


Figure 19. Indifference Curves Reflecting Interaction of Information Processing Structure and Knowledge Sharing as Contingency on Individual Learning

5. Sensitivity Analysis of Indifference Curves for Individual Learning

As with individual performance, it is possible to use Eq. (4) to provide a rudimentary sensitivity analysis of the optimal structure-contingency combination for any given stakeholders' weighting of the dependent variables *time* and *accuracy* relative to individual learning. Specifically, we can again vary α and γ according to the stakeholders' valuation strategy, ensuring that the sum of α and γ is equal to one for ease of comparison. We use the individual learning data for X_{s-c} and Y_{s-c} (see Table 42). Using this technique, we can determine which structure-contingency combination optimizes individual learning for any given value of α and γ . We can then rank each of the four possible structure-contingency combinations relative to the stakeholders' weights for α and γ . By sampling this performance space, we can provide a rudimentary sensitivity analysis for the types of indifference curves described above.

Table 43 illustrates a sensitivity analysis for indifference curves associated with individual learning. Within the table, Edge information processing structures are listed in

bold, and Hierarchy information processing structures are listed in *italics*. Moreover, teams supported by knowledge sharing are highlighted in yellow (light grey) while the teams not supported by knowledge are not highlighted.

Stakeholder Values		Rank			
<i>Multiple of Time</i>	<i>Multiple of Accuracy</i>	<i>Best</i>			<i>Worst</i>
α	γ	1	2	3	4
0.1	0.9	E-nK	E-K	H-K	H-nK
0.2	0.8	E-nK	E-K	H-K	H-nK
0.3	0.7	E-nK	E-K	H-K	H-nK
0.4	0.6	E-K	E-nK	H-K	H-nK
0.5	0.5	E-K	E-nK	H-K	H-nK
0.6	0.4	E-K	E-nK	H-K	H-nK
0.7	0.3	E-K	E-nK	H-K	H-nK
0.8	0.2	E-K	E-nK	H-K	H-nK
0.9	0.1	E-K	E-nK	H-nK	H-K

Table 43. Sensitivity of Individual Learning to Varying Stakeholder Values for Time and Accuracy

Notably, individual learning within Edge information processing structures (i.e., E-K and E-nK) ranks higher than individual learning within Hierarchy information processing structures (i.e., H-K and H-nK) as we vary α and γ . As learning how to complete one's work more quickly *decreases* in importance (e.g., $\alpha = 0.1$) and learning how to produce more accurate work *increases* in importance (e.g., $\gamma = 0.9$), the superior structure-contingency combination for individual learning appears to be the Edge information processing structure *not* supported by knowledge sharing (E-nK). However, as learning how to complete one's work more quickly *increases* in importance (e.g., $\alpha = 0.9$) and learning how to produce more accurate work *decreases* in importance (e.g., $\gamma = 0.1$), individual learning appears optimized within the Edge information processing structure supported by knowledge sharing (E-K). This finding suggests that the Edge information processing structure is conducive to individual learning overall, but that sharing knowledge may be particularly helpful for learning how to work more quickly.

For individual learning within the Hierarchy information processing structure, the results are more consistent across varying stakeholders' values. Specifically, when

assigned to Hierarchy information processing structures, the experimental data and basic sensitivity analysis illustrated in Table 43 suggest that individual learning is enhanced when subjects can share knowledge (H-K). The data also indicate that individual learning ranks worst under a variety of stakeholder valuation strategies when subjects are assigned to Hierarchy information processing structures and not provided with a mechanism for sharing knowledge (H-nK).

The near symmetry of the rankings in Table 43 yield important results. First, regardless of stakeholder weights of *time* and *accuracy*, individual learning is enhanced when subjects are assigned to Edge information processing structures (i.e., E-nK, E-K). This result implies that individual learning within teams may relate closely to the structure of team information flows. Moreover, assignment to an Edge structure moderated by knowledge sharing (E-K) enhances individual learning *most* under many stakeholder weighting options illustrated above. This nuance suggests an important second result: knowledge sharing within teams serves as an important influence to individual learning.

The pattern noted with the Edge structure (i.e., E-K, E-nK) repeats with the Hierarchy information processing structures (i.e., H-nK, H-K). Specifically, individual learning is greater when individuals are assigned to Hierarchy structures supported by knowledge sharing (H-K) than when not supported by knowledge sharing (H-nK). This experimental finding is consistent with the extant literature (e.g., March 1991; Argote 1999; Argote et al. 2003), that suggests knowledge creation and transfer are important components of individual learning within teams. However, it adds to our understanding about the relationship between learning and knowledge creation/transfer in a meaningful way through intimating that *undergirding information flows serve as an additional moderating influence on individual learning within team settings*.

D. TEAM PERFORMANCE

In this section, I discuss interaction effects of information processing structure and knowledge sharing on team performance.

1. Accuracy

The experimental data for team performance suggest that knowledge sharing may moderate the influence of information processing structure on team performance. As predicted by *Hypothesis 4*, teams supported with knowledge sharing produce more accurate work than teams not supported with knowledge sharing. This relationship holds regardless of whether the teams are configured as Edge or Hierarchy information processing structures. However, Edge teams with knowledge sharing appear to provide more accurate work than teams configured under any other experimental condition (i.e., Hierarchy with knowledge sharing, Edge without knowledge sharing, Hierarchy without knowledge sharing). Specifically, accuracy for Edge teams supported by knowledge sharing (E-K) averages 0.724 (out of 1.0) while on average, accuracy for all other team configurations ranges from 0.501 to 0.632 (out of 1.0). These results suggest that the Edge information processing structure moderated by knowledge sharing (E-K) may be uniquely poised to produce more accurate performance than other types of teams studied. Moreover, Edge teams with knowledge sharing (E-K) may produce this more accurate work more quickly, on average, than other teams.

2. Time

The experimental data also suggest that for team performance, Hierarchy teams with knowledge sharing (H-K) complete complex, interdependent tasks more slowly than other teams under study (i.e., Edge with knowledge sharing, Edge without knowledge sharing, Hierarchy with knowledge sharing). Specifically, Hierarchy teams supported with knowledge sharing (H-K) complete the task with an average time measure of 0.230, or 50.0 minutes after the start of the approximately 60-minute experimental session. In contrast, other teams complete the task with average time measures ranging from 0.366 to 0.469, or 34.5 to 41.2 minutes after the start of the experimental sessions. The data thus suggest that Hierarchy teams improve their accuracy, on average, when supported with knowledge sharing. The addition of knowledge sharing to the Hierarchy information processing structure appears to *slow down* completion of complex tasks considerably.

This combination of effects thus yields the intriguing and asymmetric result that for the Hierarchy, knowledge sharing improves accuracy while adding to the amount of time necessary for completing complex tasks. For the Edge, knowledge sharing improves accuracy while reducing the amount of time necessary for completing complex tasks. The experimental data for team performance as differentiated by combination of information processing structure and knowledge sharing are summarized in Table 44 below.

		Knowledge Sharing					
		<i>Supported</i>			<i>Not Supported</i>		
	Accuracy	μ	σ	<i>N</i>	μ	σ	<i>N</i>
Information Processing Structure	<i>Edge</i>	0.724	0.129	4	0.501	0.232	4
	<i>Hierarchy</i>	0.632	0.158	4	0.514	0.101	4
	Time	μ	σ	<i>N</i>	μ	σ	<i>N</i>
	<i>Edge</i>	0.469	0.133	4	0.366	0.062	4
	<i>Hierarchy</i>	0.230	0.098	4	0.405	0.061	4

Table 44. Comparison of Information Processing Structure Moderated by Knowledge Sharing as Contingency – Team Performance

3. Contrasts for Team Performance

This cursory examination of the team performance data suggest that two contrasts may prove particularly useful for understanding the intersection of information processing structures and knowledge sharing relative to team performance. Shapiro-Wilk and Levene's tests indicate that the contrast data are normally distributed (within group) and homogeneously variant (between group). Results of the analyses are reported in parentheses based on the *t*-test, which is appropriate for planned contrasts of parametric data. Given the contrasts below, the Bonferroni α correction would suggest rejecting the statements if $p > \frac{0.05}{3} = 0.0167$ (accuracy) and $p > \frac{0.05}{3} = 0.0167$ (time):

- E-K vs. all: Teams with Edge information processing structures moderated by knowledge sharing produce more accurate work than teams subject to all other

combinations of information processing structure and knowledge sharing ($t = 1.895$, p (one-tailed) = 0.04, $r = 0.45$, medium effect, $N = 16$)

- H-K vs. all: Teams with Hierarchy information processing structures moderated by knowledge sharing take longer to complete their work than teams subject to all other combinations of information processing structure and knowledge sharing ($t = -3.345$, p (one-tailed) = 0.0025, $r = 0.67$, large effect, $N = 16$)

These contrasts support assertions that teams with Hierarchy information processing structures moderated by knowledge sharing work (H-K) *more slowly* than teams subject to all other combinations of information processing structure and knowledge sharing, with statistically significant results. Edge teams supported with knowledge sharing (E-K) complete complex tasks with the most accurate results.

4. Indifference Curves for Team Performance

Figure 20 depicts observed team performance means based on the four experimental conditions – Edge teams moderated by knowledge sharing (E-K), Edge teams without support of knowledge sharing (E-nK), Hierarchy teams moderated by knowledge sharing (H-K), and Hierarchy teams without support of knowledge sharing (H-nK). The graph includes indifference curves in which performance with respect to time and accuracy are equally weighted. In such a performance space (i.e., when time and accuracy are equally important to stakeholders), an indifference curve further from the origin reflects more optimal performance than an indifference curve closer to the origin of the graph.

On the indifference curve reflecting the lowest performance, the graph suggests that Hierarchy teams supported with knowledge sharing (H-K) perform equally well as Edge teams not supported with knowledge sharing (E-nK). These two forms are nearly interchangeable. Hierarchy teams *not* supported with knowledge sharing (H-nK) offer a slight improvement in performance, but the improvement seems nearly negligible. Thus, the indifference curves suggest that teams subject to Hierarchy with knowledge sharing

(H-K), Hierarchy without knowledge sharing (H-nK), and Edge without knowledge sharing (E-nK) produce nearly similar performance.

Edge teams supported with knowledge sharing (E-K), however, appear to outperform all others, at least when the indifference curves weight performance relative to time and accuracy equally. Again, this assessment is overly simplistic, as stakeholder values often drive desired performance characteristics (Stainer & Stainer 1998; Stainer 2004; Driscoll & Starik 2004; van Marrewijk 2004), and indifference curves created by stakeholders may not be linear (Jones 2007). The assessment does, however, offer an example of how the influence of information processing structure and knowledge sharing on performance can be usefully compared. The experimental data thus suggest support for a theoretical model in which knowledge sharing moderates information processing structure.

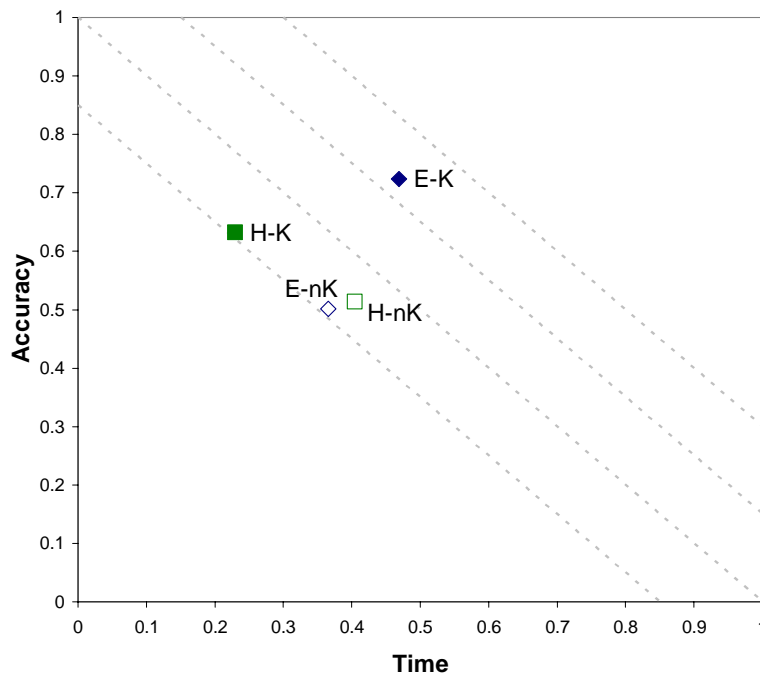


Figure 20. Indifference Curves Reflecting Interaction of Information Processing Structure and Knowledge Sharing as Contingency on Team Performance

5. Sensitivity of Indifference Curves for Team Performance

As with individual performance and individual learning, it is possible to use Eq. (4) to provide a rudimentary sensitivity analysis of the indifference curves for team performance. As previously noted, we can vary α and γ according to the stakeholders' valuation strategy, and for ease of comparison, we ensure that the sum of α and γ is equal to one. Using the team performance data for X_{s-c} and Y_{s-c} (see Table 44), we can calculate which structure-contingency combination optimizes individual learning for any given value of α and γ based on the experimental data. Ranking each of the four possible structure-contingency combinations relative to the stakeholders' weights for α and γ provides insight into the performance space for the dependent variable construct of team performance.

Table 45 illustrates a rudimentary sensitivity analysis of team performance to variance in stakeholder valuations of *time* and *accuracy*. Edge teams are listed in **bold**, and Hierarchy teams are listed in *italics*. Additionally, teams supported with knowledge sharing are highlighted in yellow (light grey) while teams not supported with knowledge sharing are not highlighted.

Stakeholder Values		Rank			
<i>Multiple of Time</i>	<i>Multiple of Accuracy</i>	<i>Best</i>			<i>Worst</i>
α	γ	1	2	3	4
0.1	0.9	E-K	<i>H-K</i>	<i>H-nK*</i>	E-nK*
0.2	0.8	E-K	<i>H-K</i>	<i>H-nK*</i>	E-nK*
0.3	0.7	E-K	<i>H-K</i>	<i>H-nK*</i>	E-nK*
0.4	0.6	E-K	<i>H-K</i>	<i>H-nK*</i>	E-nK*
0.5	0.5	E-K	<i>H-nK*</i>	E-nK*	<i>H-K</i>
0.6	0.4	E-K	<i>H-nK*</i>	E-nK*	<i>H-K</i>
0.7	0.3	E-K	<i>H-nK*</i>	E-nK*	<i>H-K</i>
0.8	0.2	E-K	<i>H-nK*</i>	E-nK*	<i>H-K</i>
0.9	0.1	E-K	<i>H-nK*</i>	E-nK*	<i>H-K</i>

* As Figure 20 illustrates, the H-nK and E-nK structure-contingency combinations appear to provide nearly equal results and thus distinctions between their relative "rankings" should be interpreted with some caution.

Table 45. Sensitivity of Team Performance to Varying Stakeholder Values for Time and Accuracy

As visual inspections of Figure 20 and Table 45 suggest, varying stakeholder values relative to *time* and *accuracy* does not change the omnibus experimental result. Expressly, when teams are structured with Edge information processing structures and supported by knowledge sharing (E-K), teams, on average, outperform other structure-contingency combinations (i.e., E-nK, H-K, and H-nK). As stakeholder values relative to *time* and *accuracy* vary, however, the *second* most optimal structure-contingency combination for team performance also varies – i.e., changing from Hierarchy supported by knowledge sharing (when accuracy of response is emphasized) to Hierarchy not supported by knowledge sharing (when timeliness of response is emphasized). If *accuracy of response* is of the utmost concern to stakeholders, for example, the structure-contingency combinations of Edge with knowledge sharing (E-K) or Hierarchy with knowledge sharing (H-K) serve stakeholders’ interests “best.” If *timeliness of response* is of the utmost concern to stakeholders, however, teams with Edge information processing structures and moderated by knowledge sharing (E-K), followed by the either information processing structure *not* supported by knowledge sharing (i.e., E-nK, H-nK), seem to support stakeholder preferences best. Under all stakeholders’ valuation strategies illustrated (see Table 45), however teams with Edge structures supported by knowledge sharing (E-K) outperform all other structure-contingency combinations (i.e., E-nK, H-K, and H-nK).

6. Failure to Complete Complex, Reciprocally Interdependent Task

The discussion on data coding and measurement (Chapter IV) revealed that one primary difference between dependent variable data at the individual versus team levels of analysis is that the team data include *non-responses by team members*. Specifically, if a team member fails to identify the details of an impending terrorist attack (i.e., fails to complete the task), his or her response is coded as zero for both time and accuracy (i.e., worst possible performance) before the team data measures are calculated. As stated in the previous chapter, there exist 24 cases in which subjects fail to complete the assigned task.

Specifically, the magnitude of failing to complete the task is roughly similar under the Edge and Hierarchy structures. Under both information processing conditions (i.e., Edge, Hierarchy), individuals fail to complete the task approximately 12 times, a result that is roughly equal in both number and percentage of observations under each condition. In contradistinction, the magnitude of failing to complete the task is uneven under the knowledge sharing manipulation. Specifically, when subjects are assigned to teams that share knowledge, the failures number seven. When subjects are assigned to teams that are not supported by knowledge sharing, the failures number 17. These results suggest that knowledge sharing influences task completion, and moreover, that the *interaction* of information processing structure and knowledge sharing may help to explain task failures. Table 46 summarizes these results, and the percentage of failures relative to the number of observations under each experimental condition is included in the table below.

		Information Processing Structure					
		<i>Edge</i>		<i>Hierarchy</i>		Total	
Knowledge Sharing		<i>N</i>	%	<i>N</i>	%	<i>N</i>	%
	<i>Supported</i>	1	1.5%	6	8.8%	7	5.2%
	<i>Not supported</i>	11	19.3%	6	14.3%	17	17.2%
	Total	12	9.7%	12	10.9%	24	10.3%

Table 46. Cross-tabulation of Failures to Complete Task

The summary in Table 46 helps explain somewhat divergent results between the indifference curves for individual and team performance. Specifically, the cross-tabulation of task completion failures suggest that one strength of the Edge information processing structure *when supported with knowledge sharing* (E-K) is that a greater percentage of individuals complete the task relative to those assigned to all other structure-contingency combinations. In contrast, the Edge information processing structure, when *not* supported with knowledge sharing (E-nK), appears to underperform all other structure-contingency combinations in terms of individual task completion. Within the two Hierarchy structure–contingency combinations, the differences are more subtle, but still striking. When the Hierarchy is moderated by knowledge sharing (H-K),

a greater percentage of subjects respond than when the Hierarchy is not moderated by knowledge sharing (H-nK). Further work is clearly needed in this area, but it seems clear that moderating the Edge information processing structure with knowledge sharing (E-K) creates a structure-contingency combination that 1) not only facilitates higher relative performance over other structure-contingency combinations, but 2) also more ably facilitates task completion by individuals assigned to it.

E. DISCUSSION

In this section, I briefly summarize findings from the planned contrasts that examined interaction effects on the dependent variable constructs of individual performance, individual learning, and team performance. I also discuss implications derived from indifference curves for each dependent variable construct in which time and accuracy are weighted equally into a compound performance criterion for complex, reciprocally-interdependent tasks. Table 47 collates the results of the planned contrasts.

1. Individual Performance

The experimental data suggest that individuals within Hierarchy teams supported by knowledge sharing (H-K) complete complex tasks *more slowly* than similar individuals assigned to any other combination of information processing structure and knowledge sharing studied. The differences between individuals assigned to Hierarchy teams supported by knowledge sharing (H-K) against all other structure-knowledge sharing combinations are statistically significant, and moreover, they reflect medium effect sizes. Put simply, individuals working within Hierarchy teams, when supported with knowledge sharing, work more slowly than counterparts assigned to any other structure-knowledge sharing combination. This result lends support to a theoretical model in which knowledge sharing moderates the relationship between information processing structure and performance, particularly relative to how quickly individuals complete their complex tasks with reciprocally interdependent information inputs.

Moreover, the indifference curves for individual performance (Figure 18) in which time and accuracy are weighted equally as performance criteria are illuminating.

The planned contrasts yield only one statistically significant effect (i.e., that individual performance is *slowest* when subjects are assigned to Hierarchy teams supported by knowledge sharing) when the Bonferroni correction is applied. However, the indifference curves for individual performance and small p -values for the other contrasts are even more suggestive that the *interaction* of information processing structure and knowledge sharing offers an important theoretical basis for understanding individual performance.

Specifically, Figure 18 suggests that for individual performance, the interaction of structure and contingency is explanatory. When individuals are assigned to Edge structures (i.e., low centralization, low formalization, and low vertical differentiation) moderated by knowledge sharing (E-K), their performance, on average, outperforms similar individuals assigned to all other conditions. When individuals are assigned to Hierarchy structures (i.e., high centralization, high formalization, and high vertical differentiation) moderated by knowledge sharing (H-K), their performance, on average, underperforms similar individuals assigned to all other conditions.

2. Individual Learning

Individual learning also appears to be influenced by the interaction of information processing structures and knowledge sharing. Specifically, individuals working within Edge information processing structures supported by knowledge sharing (E-K) learn how to work more quickly than counterparts assigned to alternate structure-knowledge sharing combinations. This finding is statistically significant with a small effect size. Like the contrasts for individual performance and team performance, the contrasts for individual learning suggest that the theoretical model in which knowledge sharing moderates the relationship between information processing structure and knowledge sharing offers a useful way of organizing these relationships.

Additionally, similar to the dependent variable construct of individual performance, the indifference curves for individual learning (see Figure 19) offer an intriguing interpretation of the experimental results. With improvement in time and improvement in accuracy weighted equally, the indifference curves suggest that the Edge

is a superior form for assisting individuals to learn, and moreover, that the Edge structure moderated by knowledge sharing (E-K) assists individual learning *most*. Moreover, the Hierarchy structure is an inferior form for assisting individuals to learn, and the Hierarchy structure *not* moderated by knowledge sharing (H-nK) results in the *least* individual learning.

Comparing these assessments against the individual performance data, we see that *comparative performance* among individuals assigned to Edge and Hierarchy structures *not* supported by knowledge sharing *is roughly equal* (i.e., for individual performance, $E-nK = H-nK$). However, *comparative learning* among individuals assigned to the same experimental conditions is quite asymmetric – when individual within the Edge structure is not supported with knowledge sharing, individuals learn at a greater rate than when individuals within the Hierarchy structure is not supported with knowledge sharing (i.e., for individual learning, $E-nK > H-nK$). The data suggest that while explicit knowledge sharing is an important component of individual learning, a team's undergirding information flows are also critically important.

3. Team Performance

Hierarchy teams complete tasks *more slowly* when supported with knowledge sharing (H-K) than any other structure-knowledge sharing combination under study. Moreover, this difference is statistically significant with a large effect size. It thus appears that Hierarchy teams may find it difficult to absorb the additional work of sharing knowledge among their members without increasing the time required to complete a complex task in which the information inputs create reciprocal interdependence. Enabling knowledge sharing within Hierarchy teams assists with production of more accurate work but considerably slows the completion of the task. This result again lends support to a theoretical model in which knowledge sharing moderates the relationship between information processing structure and team performance.

The indifference curves for team performance in which time and accuracy criteria are equally weighted (see Figure 20) are striking. The results suggest that the Edge form *when moderated by knowledge sharing* outperforms all other structure-contingency

combinations at the team level of analysis. The other three structure-contingency combinations (Edge team not supported by knowledge sharing, Hierarchy team not supported by knowledge sharing, Hierarchy team supported by knowledge sharing) offer relatively equal team performance. These results suggest that *infusing the Hierarchy information processing structure with knowledge sharing may not produce expected performance enhancements* when teams undertake complex tasks in which the information inputs are reciprocally interdependent. More broadly, the data suggest that a theoretical model in which the *interaction* of structure and contingency are emphasized offers important explanatory power for understanding team performance.

4. Implications for Team Design

The extant literature observes that the distribution of knowledge within collectives (e.g., teams, groups, organizations, networks, others) can be “clumpy” and uneven (Nissen 2006). Given the experimental results, it seems plausible that uneven distributions of knowledge may in part relate to the underlying information processing structures within collectives. If information flows are restrictive (e.g., highly centralized, highly formalized), then knowledge – like the information carrying the knowledge between one agent to another – may become lodged and perhaps attenuate somewhere within the collective, leading to suboptimal performance. Similarly, if information flows are random, needed knowledge is unlikely to reach the agents whom would benefit from it more than others, again leading to suboptimal performance. However, if information flows reflect instantiations of limited structure (e.g., low centralization, low formalization; see also Brown & Eisenhardt 1997, Nissen 2007a), then the *interaction* of structure and knowledge sharing leads to outperformance.

From resource and design intervention perspectives, managers that invest in knowledge creation and storage (e.g., professional education, critical knowledge repositories, expert systems) may not realize the expected benefit of improved performance unless team information flows are organized in a manner to support transfer of actionable information (i.e., knowledge) between team members. Managers of knowledge workers may thus wish to strike a careful balance between the accumulation

of knowledge within individual parts of collectives (e.g., knowledge stocks held by a particular team member) and the collective's capacity for sharing that knowledge (i.e., structuring information flows to support knowledge transfer). The experimentation suggests that applying resources or design interventions *only* toward the former *or* toward the latter is unlikely to produce sizable performance gains; applying resources or design interventions toward both would likely prove more fruitful for enhancing performance when the collective's work generally involves undertaking complex, reciprocally interdependent tasks.

	Significance	Effect size	Test	Assessment
Individual Performance				
E-K vs. E-nK: <i>Accuracy: Individuals produce more accurate results when assigned to Edge teams supported by knowledge sharing than when assigned to Edge teams not supported by knowledge sharing</i>	$p = 0.02$	Small	Mann-Whitney U	Bonferroni correction suggests statement is not supported, but small p value indicates future work might prove fruitful
H-K vs. H-nK: <i>Accuracy: Individuals produce more accurate results when assigned to Hierarchy teams than when assigned to Hierarchy teams not supported by knowledge sharing</i>	$p = 0.036$	Small	Mann-Whitney U	Bonferroni correction suggests statement is not supported, but small p value indicates future work might prove fruitful
E-K vs. H-K: <i>Accuracy: Individuals produce more accurate results when assigned to Edge teams supported by knowledge sharing than when assigned to Hierarchy teams supported by knowledge sharing</i>	$p = 0.049$	Small	Mann-Whitney U	Bonferroni correction suggests statement is not supported, but small p value indicates future work might prove fruitful

	Significance	Effect size	Test	Assessment
E-K vs. H-K: <i>Time: Individuals work more quickly when assigned to Edge teams supported by knowledge sharing than when assigned to Hierarchy teams supported by knowledge sharing</i>	$p < 0.001$	Large	Mann-Whitney U	Supported
All others vs. H-K: <i>Time: Individuals work more quickly when assigned to all other types of teams than when assigned to Hierarchy teams supported by knowledge sharing</i>	$p < 0.001$	Medium	Mann-Whitney U	Supported
Individual Learning				
E-nK vs. All others: <i>Accuracy: Individuals learn to produce more accurate work when assigned to Edge teams not supported by knowledge sharing than when assigned to all other types of teams</i>	$p < 0.001$	Small	Kolmogorov-Smirnov Z	Supported
All others vs. H-nK: <i>Accuracy: Individuals learn to produce more accurate work when assigned to all other types of teams than when assigned to Hierarchy teams not supported by knowledge sharing</i>	$p = 0.027$	Small	Kolmogorov-Smirnov Z	Bonferroni correction suggests statement is not supported, but small p value indicates future work might prove fruitful
E-K vs. All others: <i>Time: Individuals learn to complete their work more quickly when assigned to Edge teams supported by knowledge sharing than when assigned to all other types of teams</i>	$p < 0.001$	Small	Kolmogorov-Smirnov Z	Supported
Team Performance				

	Significance	Effect size	Test	Assessment
E-K vs. All others: <i>Accuracy: Edge teams supported by knowledge sharing produce more accurate work than all other types of teams</i>	$p = 0.04$	Medium	t -test	Bonferroni correction suggests statement is not supported, but small p value and medium effect size indicate future work might prove fruitful
All others vs. H-K: <i>Time: All other types of teams complete their work more quickly than Hierarchy teams supported by knowledge sharing</i>	$p < 0.01$	Large	t -test	Supported

Table 47. Summary of Planned Contrasts for Interaction Effects

F. SUMMARY

In this chapter, I explored how the interaction of information processing structure and knowledge sharing influence individual performance, individual learning, and team performance using planned contrasts suggested by cursory examinations of the data and analyses of the main effects. The results are intriguing and suggest support for my theoretical model, which posits that knowledge sharing moderates the relationship between information processing structure and performance. More specifically, the results suggest that infusing a team with a capacity for knowledge sharing may not yield expected changes in performance *unless the team's information processing structure is organized in a manner such that the added value of creating and sharing knowledge across the team can be realized*. This assessment is supported at both the individual and team levels of analysis.

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VII. CONTRIBUTIONS AND SUGGESTIONS FOR FURTHER INVESTIGATION

In the previous chapters, I explored the main and interaction effects of information processing structures and knowledge sharing on performance and learning. The investigation was guided by nine hypotheses derived from a theoretical model in which knowledge sharing moderates the relationship between information processing structure and performance. Conclusions were based on a series of laboratory experiments in which four teams complete relatively similar complex tasks with reciprocally interdependent information inputs over a period of 36 days.

As the model predicts, knowledge sharing moderates the relationship between information processing structure and performance. Specifically, the interaction of information processing structure and knowledge sharing serves as a useful predictor of variance within individual performance, individual learning and team performance. The interaction of information processing structure and knowledge sharing did not serve as a useful predictor for variance in team learning. Empirical data from the experimentation suggest that if teams undergo restructuring of their information flows, the direction of structural transformation is critically important to subsequent performance—moving from an organic information processing structure (i.e., low centralization, low formalization and low vertical differentiation) to a mechanistic information processing structure (i.e., high centralization, high formalization and high vertical differentiation) degrades performance when working on complex, interdependent tasks. However, transforming from a mechanistic information processing structure to an organic information processing structure significantly improves performance.

In this chapter, I summarize the major contributions of my work, and highlight four postulates derived from the experimentation. I briefly outline multiple possible future research paths that could be motivated by my findings. These paths include extensions of the theoretical model as well as interpretation of the experimentation via a number of alternate theoretical lenses. I close by summarizing the work as a whole. Short portions of the text are adapted from Leweling and Nissen (2007b).

A. CONTRIBUTIONS

In this section, I highlight some of the contributions of my work. I begin by discussing my theoretical model, which integrates three related but independent theoretical traditions of structural contingency theory, information processing theory and knowledge flows theory. I particularly emphasize the meaning of this intersection for the concept of fit relative to the theoretical streams informing my work, and I discuss empirical testing of the theoretical model via the ELICIT experimental protocol. I then outline important findings from the laboratory experimentation, summarizing them in the form of empirically-derived postulates. I close by discussing how this work contributes to ongoing research.

1. Theoretical Model as Unique Intersection

In this section, I discuss how my theoretical model contributes to theorizing about collective performance. I include a discussion of the concept of fit as it pertains to the theoretical intersection motivating my work. I then highlight the contribution of my model to contemporary interpretations of structure and contingency within structural contingency theory.

a. Fit within Three Theoretical Traditions

The concept of fit serves as a common link between structural contingency, information processing and knowledge flows theorizing. At an elementary level, structural contingency theory proposes that some organizational structures fit to various contingencies better than alternates, resulting in higher performance. Likewise, information processing theory suggests that some information processing structures fit highly uncertain (e.g., complex and interdependent) environments better than others, leading to outperformance. Knowledge flows theorizing similarly asserts that organizations that fit knowledge flows to work flows outperform organizations that do not. Fit, then, is an important concept in all three theoretical traditions. As a self-standing concept, however, fit is often loosely defined and varyingly operationalized.

b. Fit within Theory Development

From a perspective of theory development, for example, Venkatraman (1989) views fit as explicitly linking verbalized theoretical relationships to analysis of empirical data. Venkatraman (1989) differentiates concepts of fit into six types—fit as moderation, mediation, profile deviation, gestalts, covariation, and match. He suggests that focus on interaction effects is appropriate when fit “between the predictor and the moderator is the primary determinant of the criterion variable” (p. 424), as in the case in my theoretical model. This view of fit, scholars argue, is particularly useful for research designs grounded in contingency theory (Schoonhoven 1981 p. 351; Gupta & Govindarajan 1984; Venkatraman 1989), and allows relationships between organizational structure and various environmental task characteristics to be differentiated along the latent dimension of fit-misfit (Burns & Stalker 1961; Lawrence & Lorsch 1967; Baligh et al. 1996; Birkinshaw et al. 2002; Burton & Obel 2004). From both the theoretical and empirical perspective, the research presented in this work is consistent with the view of fit as explicating a moderating relationship between structure (e.g., information flows) and contingency (e.g., knowledge sharing). This choice reflects careful consideration of the meaning of fit within my work, and is consistent with Venkatraman’s (1989) observations about the appropriateness of “fit as moderating” for contingent-theoretic designs.

c. Fit within Strategic Management

Miller (1992), however, views fit differently. For Miller (1992), fit refers to the compatibility of an organization’s *external* contingency-theoretic fit (i.e., structure fits environment) with an organization’s *internal* fit (i.e., structure fits strategy). Specifically, Miller’s (1992) work finds support for postulates that in organizations suited to uncertain task environments, structure and strategy are loosely coupled (resulting in flexible structures), while in organizations ill-suited to uncertain task environments, structure and strategy are tightly coupled (resulting in inflexible structures). Within contingency theory, then, fit refers to the relationship between structure and contingency,

while within the strategic management literature, fit often refers to the relationship between structure and strategy.

d. Fit within Organizational Psychology and Teams

In the organizational psychology and team literatures, the concept of fit has also produced a long and fruitful research stream, often focused on person-organization fit (for a review, see Kristof 1996; see also Westerman & Cyr 2004). Kristof (1996) categorizes person-organization fit into two types: supplementary (i.e., personal characteristics, such as personality, fit with organizational characteristics, such as culture) and needs-supplies (e.g., personal skills fit with organizational skill deficiencies). Kristof (1996) further differentiates person-organization fit from other types of fit, such as person-vocation (e.g., self-concept fits vocational selection), person-group (e.g., individual demography fits team composition) and person-job (e.g., individual knowledge and skills fit assigned tasks). The concept of fit is thus clearly useful within many theoretical traditions and at multiple levels of analysis, suggesting that an omnibus operationalization of fit is unlikely among the literatures that seek to explain collective performance as well as the literatures that seek to explain individual performance within collective action.

e. Fit at Unique Theoretical Intersection

Nonetheless, the research presented in this work provides an opportunity to consider fit at the intersection of three theoretical traditions—structural contingency theory, information processing theory and knowledge flows theory. Following Hollenbeck et al.'s (2002) contention that theorizing about work teams could benefit from greater exploration of how team structures fit tasks (as opposed to a more traditional topic within the team literature of how individual demography fits team composition), I view structure with an information processing lens, drawing from a long tradition of viewing organizations as information processing systems (March & Simon 1958; Galbraith 1974/1977; Orlikowski & Robey 1991). To define team structure via this lens, I leverage dimensions of structure long established in the organizational literature (i.e.,

centralization, formalization, and vertical differentiation). These dimensions form a design space (Tushman & Nadler 1978; Daft & Lengel 1986; Gateau et al. 2007) for comparing archetypal structural forms that draws from and extends related conceptualizations about the meaning of structure within an information processing view of organizing (e.g., Levitt et al. 1994; Levitt et al. 1999). The “structure” of structural contingency theory thus becomes operationalized within a team’s information processing mechanisms, consistent with knowledge-based views of the firm (Grant 1996b; Spender 1996; Grant & Spender 1996; Nonaka et al. 2000) and Orlikowski’s (1992, 2001) conception of information technology as an integral, analytically intractable part of organizational structuration.

More recent work has established the important role of knowledge creation and transfer within organizational performance (March 1991; Eppler & Sukowski 2000; Jarvenpaa & Staples 2000; Gold et al. 2001; Lee & Choi 2003). Integrating knowledge flows theorizing (Nonaka 1994; Nonaka & Takeuchi 1995; Nissen 2006) into the theoretical framework builds on previous work that identifies knowledge as an important contingency variable for organizations and teams (Rulke & Galaskiewicz 2000; Becerra-Fernandez & Sabherwal 2001; Birkinshaw et al. 2002; Hutzschenreuter & Listner 2007). Knowledge sharing thus comes to represent “contingency” in a structural contingency framework in which fit is conceptualized as observed performance when a team’s information processing structure is moderated by knowledge sharing. In this sense, the research presented in this dissertation unpacks, rearranges, integrates, and then extends existing theorizing (e.g., Levitt et al. 1994; Levitt et al. 1999; Birkinshaw et al. 2002; Hollenbeck et al. 2002) about how team information processing structures, as moderated by knowledge sharing, fit together to influence performance.

This integration is codified within a theoretical model that explains collective performance by arranging contingency as moderator to the relationship between structure and performance. The theoretical model thus contributes to an ongoing discourse (e.g., Huber 1990; Orlikowski & Barley 2001; Lee & Choi 2003) about the meaning of important concepts such as structure and contingency when collective action is viewed through information processing and knowledge flows lenses. As such, part of

my contribution to the academy is a cogently developed and articulated conceptual model that seeks to enhance the explanatory power of previous empirical work identifying knowledge as a contingency variable for collective performance. Moreover, the structural contingency framework and information processing lens offers a useful way of organizing theoretical relationships and comparing empirical findings on related topics. The resultant model is novel, and yet carefully grounded in the literature of the domains from which it is drawn. It proposes a compact but useful way of thinking about important antecedents to collective performance using core concepts from the information sciences disciplines – the structure of information flows and the importance of knowledge transfer.

2. Empirical Analysis

In this section, I briefly recap the operationalization of my model within the experimentation, highlighting the importance of empirical investigation for developing and refining theory.

a. Scientific Inquiry

Hughes et al. (1986) suggest theory development should be integrated with empirical investigation, and as such, one of my contributions to the scholarly discourse is the empirical analysis of my theoretical model. Specifically, as I developed the theoretical model, I motivated nine hypotheses for empirical investigation. These hypotheses provide a structured way for testing the model and assessing whether its introduction offers a meaningful contribution to existing research streams. Such testing is consistent with a view of scientific theory “as a complex spatial network in which hypotheses link theoretical constructs one to another, correspondence rules link theoretical constructs to derived and empirical concepts, and derived and empirical concepts are given meaning through operational definition.” (Hughes et al. 1986 p. 128; see also Hempel 1962; Salmon 1978; Bagozzi & Phillips 1982; Salmon 1992)

b. Laboratory Environment

I tested nine hypotheses with experimentation using human subjects in a highly calibrated laboratory setting. The ELICIT multi-player intelligence game (Parity 2006; Lospinoso & Moxley 2007) creates an experimental environment in which teams of up to 17 subjects can be closely observed solving a complex task. Within the experimentation, the initial information inputs are distributed in a manner to create reciprocal interdependence among the participants. The subjects' task environment is thus complex and reciprocally interdependent. The ELICIT software also serves as one of the primary data collection instruments, allowing micro-level behaviors—including completion of the assigned task—to be logged to the nearest second.

c. Operationalizations

Within the laboratory environment, I created two team information processing structures for experimentation: organic (i.e., Edge, with low centralization, low formalization, and low vertical differentiation) and mechanistic (i.e., Hierarchy, with high centralization, high formalization and high vertical differentiation). Through the introduction of the experimental device of a “postcard,” I also created two knowledge sharing conditions—supported and not supported. These explicit operationalizations of information processing structure and knowledge sharing assisted in transforming my theoretically-motivated concepts into operationalized constructs (Kerlinger & Lee 2000 p. 40), allowing for empirical testing of the theoretical model.

d. Manipulations

Experimentation proceeded by manipulating the independent variables of structure and contingency with four teams playing four different versions of the game over 36 days of experimentation (see Table 10 for the manipulation sequence). Time and accuracy served as the dependent performance measures (see Table 13 for a summary of independent and dependent variables), allowing for comparison of individual performance, individual learning, team performance and team learning under various combinations of information processing structure and knowledge sharing conditions. The

carefully constructed laboratory setting thus provided an opportunity to assess the utility of the theoretical model subjected to a counterbalanced manipulation sequence. The results of this experimentation are summarized below. As the discussion above indicates, a second contribution of my work is the explicit operationalization of the theoretical model into a testable construct.

3. Key Results

In this section, I summarize some of the important results of the experimentation into four empirically-derived postulates. I begin with a discussion of the relationship between information processing structure and knowledge sharing. I then discuss the bi-directional effect of structural transformation on team performance, and I close with contrasting the interactive influence of information processing structure and knowledge sharing on performance versus learning.

a. Interaction of Information Processing Structure and Knowledge Sharing

Modern organizations, many scholars argue, create (and sustain) competitive advantage through successfully creating and transferring knowledge across various boundaries— interpersonal (e.g., Reagans & McEvily 2003), intergroup/interteam (e.g., Darr et al. 1995; Hansen 1999; Argote & Ingram 2000), and interorganizational (e.g., Dyer & Nobeoka 2000; Kotabe et al. 2003; Wang et al. 2004). However, following Polanyi (1975), Nonaka (1994) argues that knowledge creation occurs within individuals, not organizations. Organizations generate competitive advantage by successfully facilitating knowledge creation within individuals and assisting individuals to transfer that knowledge to others. March (1991) argues that knowledge can be stored within organizational codes and then distributed to members via “various forms of instruction, indoctrination and exemplification” (p. 74). One of the possible mechanisms through which collectives facilitate the transfer of knowledge, then, is to store knowledge within its codes or routines, allowing individuals to asynchronously access the knowledge as required.

In contrast, Nonaka and Takeuchi (1995) argue that “information is a flow of messages, while knowledge is created by that very flow of information, anchored in the beliefs and commitment of its holder” (pp. 58-9). Nonaka and Takeuchi’s (1995) argument thus implies an interpretation of March (1991) in which collectives store *information* within their codes and routines. The *flow of information between the individual and the routine*, combined with the individual’s ability to contextualize the information (Tsoukas & Vladimirou 1999; Nissen 2006), allows the individual to act. Taking appropriate action provides the observable behavior that intimates knowledge held by others throughout the collective has been recreated within the individual, reflecting an understanding and reinforcement of the collective’s socially-constructed meaning system for interpreting stimuli. Consistent with Polanyi (1975) and Nonaka (1995), knowledge is held by the individual, but the knowledge “makes sense” only within the organizational context. Organizational routines contribute to the collective sensemaking by structuring the underlying information flows for sharing and recreating knowledge.

This view is consistent with Tsoukas and Vladimirou (2001), who describe an epistemic position in which organizational knowledge “...is thought to be profoundly collective, above and beyond discrete pieces of information individuals may possess; it is a pattern formed within and drawn upon a firm, over time.” (p. 975) Combined, the perspectives of March (1991), Nonaka and Takeuchi (1995), Tsoukas and Vladimirou (2001) and Nissen (2006), suggest characterizing organizational knowledge in some fundamental ways. First, *organizational knowledge* is created and recreated by individuals, and knowledge creation and transfer can enhance individual and collective performance. Second, organizational knowledge is shared through an organization’s information flows. If stable, these information flows can form patterns. Third, these patterns suggest that the undergirding *structure* of information flows may influence a collective’s capacity for transferring knowledge between one organizational agent to another.

A synthesis of these characterizations suggest that the structuration of information flows—which I have expressed as “information processing structures”

throughout discussions of the theoretical model—should serve as a significant influence on the collective capacity to create and transfer knowledge. If “information is a flow of messages” (Nonaka & Takeuchi 1995 p. 58), then the structure of the information flows should influence the ability of individuals to create (and recreate) knowledge and for collectives to transfer knowledge among their memberships. This interpretation of prior work informs two principal postulates to emerge from the experimentation:

Postulate 1. *The structure of information flows influences the speed at which knowledge is transferred.*

Postulate 2. *The combination of information processing structure and knowledge transfer influences performance.*

Knowledge creation and transfer are intrinsically linked to collective information flows; the underlying pattern of these information flows influences a collective’s capacity for transferring knowledge. Moreover, the interaction of these information flows and knowledge transfer affects performance.

Evidence for these postulates is suggested by the outcomes of individual performance and team performance within the experimentation, particularly as they relate to the testing of *Hypotheses 1, 1a, 4 and 4a*, as well as the *interaction* between manipulating information processing structure and manipulating the knowledge sharing condition. Without a full recapitulation of the statistical analyses, consider a basic ordering system in which each structure-contingency combination is ranked relative to the other according to the mean values on the performance dimensions of time and accuracy. In such a system, the “best” mean performance (in the case of the experimentation, the mean closest to 1.0) would receive a ranking of one, the next “best” relative mean performance would receive a ranking of two, and so on. Performance in which time and accuracy are equally weighted could involve adding the rank values, resulting in a compound performance criterion that ranges from a minimum of two (best possible performance) to eight (worst possible performance). Figure 21 illustrates such a schema for the results of the individual performance.

	Edge	Hierarchy
Supported	1	4
Not Supported	3	2
Time		

+

	Edge	Hierarchy
Supported	1	2
Not Supported	3	4
Accuracy		

⇒

	Edge	Hierarchy
Supported	2	6
Not Supported	6	6
Combined Performance		

Figure 21. Rank Order of Mean Individual Performance

As illustrated in Figure 21, individuals participating within either organic (i.e., Edge) or mechanistic (i.e., Hierarchy) information processing structures supported by knowledge sharing (in yellow) provide more accurate results than similar individuals participating in teams not supported by knowledge sharing (in white). Moreover, for individuals within organic structures with knowledge sharing, the task is completed quickly (in green); for individuals within mechanistic structures without knowledge sharing, the task is completed slowly (in orange). When the individual performance rankings are combined such that both dimensions of performance equally weighted, it appears that the mechanistic (i.e., Hierarchy) structure *could not support* knowledge sharing among its members without slowing its responsiveness (in lavender) to a level that makes its *overarching* performance equal to teams not supported by knowledge sharing. In contrast, the organic (i.e., Edge) structure appears to easily absorb the additional work of sharing knowledge among its members and excels as a result. If team information processing structures do not adequately support knowledge sharing, creating a capacity to transfer knowledge within teams may result in individual performance at the same level as if knowledge sharing was not supported at all.

This relationship also holds for team performance, as illustrated in Figure 22 below, and represents one of the significant findings within the experimentation. Put simply, at both the individual and team levels of analysis, structure and contingency *interact* to influence performance. Additionally, while further investigation would likely prove fruitful, it appears plausible that the *combination of* Edge information processing structures with knowledge sharing offers parallels to Brown and Eisenhardt's (1997, 1998) descriptions of organizational forms with *sufficient but not overburdening structures*. These structures, Brown and Eisenhardt (1997, 1998) contend, enable adaptation through near-instantaneous communications and as the experimentation

described herein suggests, asynchronous access to important collective information stores. Deriving their findings from case studies, Brown and Eisenhardt (1997) contend that such organizational forms are important for sustaining competitive advantage in complex, turbulent environments. The experimentation describe here complements their work by operationalizing elements of limited structure (e.g., low centralization, low formalization) through an information processing lens within a laboratory setting. I then specifically test the influence of these selected structural elements on performance and learning.

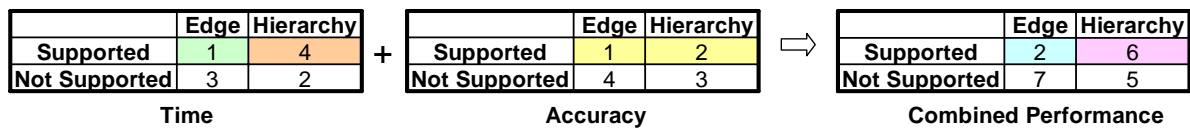


Figure 22. Rank Order of Mean Team Performance

b. Team Performance under Structural Transformation

The postindustrial society, Mohrman and Mohrman (1989) argue, “is characterized by increasing complexity and interconnectedness and by an unrelenting rate of change,” requiring organizations to “chang[e] their design as they go.” (p. 272) Using the metaphor of improvisational theater, Weick (1993b) similarly describes organizational redesign as a “continuous activity” (p. 347) in which dimensions of organizational structure serve merely as a static representations of relentlessly modified organizational processes. In Weick’s (1993b) view, structural stability is elusive; change is *de rigueur*. Huber et al. (1993) consider structure as a moderately useful predictor of organizational change, but in related work, Glick et al. (1990) note that structure can serve as an indicant of change, as when control or incentive systems within organizations are modified. Focused on the *process* of change, MacIntosh and MacLean (1999) draw from complex systems theory to prescribe a three-stage process of conditioning, disequilibrium and feedback for transforming from one organizational archetype to another. Similarly, Salem (1999) suggests morphogenesis (i.e., emergence, divergence, transformation and convergence) as a multi-level descriptor for paths toward increasingly

more complex organizational systems. Alternatively, Cummings and Worley (1993), as summarized in Whelan-Berry et al. (2003), describe a model of organizational change that involves rousing commitment, crafting a shared image of outcome, engendering political support, managing transition states and maintaining the impetus for change until completion. These interpretations of organizational change, while diverse and varying in their theoretical intent (i.e., description, prescription, explanation, evaluation), suggest that structural transformation within organizations persists as an important topic within organizational studies.

Whelan-Berry et al. (2003) argue that organizational change “cannot occur ... without teams and individual employees adopting different work routines or processes and different models, frameworks or values to guide their actions” (p. 187). Whelan-Berry et al. (2003) thus imply that organizational change likely involves the restructuring of team processes. Team structure can refer to the demography of a team’s membership (e.g., Michel & Hambrick 1992; Keck & Tushman 1993; Smith et al. 1994; Keck 1997; Lawrence 1997), but an emerging, if somewhat fragmented, research stream defines team structure along dimensions similar to traditional components of organizational structure (e.g., Priem 1990; Stewart & Barrick 2000; Prasad & Akhilesh 2002). For example, Stewart and Barrick (2000), invoking a resource-based view of the firm, describe team structure as “team relationships that determine the allocation of tasks, responsibilities and authority.” (p. 135) Alternatively, drawing from classic studies of the influence of group communication structures on team outcomes (e.g., Bavelas 1950; Leavitt 1951; Guetzkow & Simon 1955); the relationship between interdependence, uncertainty and organizational information processing (Thompson 1967; Galbraith 1974; Galbraith 1977; Tushman & Nadler 1978; Tushman 1979; Premkumar 2005); and re-interpretations of long-standing dimensions of organizational structure within knowledge-based views of the firm (Grant 1996b; Grant & Spender 1996; Spender 1996), team structures are also viewed through an information processing lens (e.g., Huber et al. 1975; Levitt et al. 1994; Wong & Burton 2000). This lens enables Stewart and Barrick’s (2000) team structure to be viewed in terms of information flows rather than authority arrangements, consistent with Grant’s (1996b) emphasis on coordination rather than cooperation as the primary

motivational problem for knowledge-based views of the firm. Combined with Hollenbeck et al.'s (2002) suggestion that structural contingency theory be extended to team level studies in order to emphasize how teams fits to task and MacIntosh and MacLean's (1999) view of organizational change as the transition from one deep structure/archetype to another (see also Ranson et al. 1980), the experimentation undertaken as part of this dissertation appears to offer some rudimentary findings for the organizational change and team structure literatures.

Specifically, another exciting and noteworthy finding to emerge from the experimentation is the bi-directional and asymmetrical influence of restructuring team information processes on subsequent performance. As discussed in previous chapters, the data provide support for summarizing the laboratory results related to structural transformation in the form of a third postulate:

***Postulate 3.** Restructuring information flows influences performance asymmetrically.*

During the experimentation, the transition from a mechanistic information processing structure to an organic information processing structure resulted in considerably enhanced performance. However, the converse transition – i.e., from an organic to a mechanistic information processing structure – significantly degraded subsequent performance. Changing from Edge to Hierarchy, it seems, requires a team to revamp and reform its information processing structures to adapt to the new “deep structure,” resulting in degraded performance until the transition is complete and team members have adapted to the change. Altering from Hierarchy to Edge, however, allows a team to not only retain its existing “deep structure,” but also add new information flows to its work processes, resulting in more effective performance. Once the transformation was complete (e.g., at subsequent assignment of a similar task), however, both teams improved their performance significantly between the third and fourth sets of experiments. These results suggest that the impact of interrupting team routines (see

Zellmer-Bruhn 2003) on immediate performance may depend upon the teams' underlying information processing structures.

While preliminary and limited to a small sample size,²³ the results are nonetheless promising and worthy of further investigation. Responsiveness of teams to change, for example, may reflect a dependency upon team members retaining access to pre-existing information flows during the transition period as new information processes are established. Such assertions, however, require grounding in multi-level theorizing about individual-team information processing relationships and more detailed empirical explorations. The experimentation also suggests that computer-mediated games in which software assists researchers to observe micro-level team interactions, as well as records behaviors of interest by participants, can serve as effective platforms for exploring structural transformation within teams, contributing to full-cycle theorizing (Chatham & Flynn 2005). Further, studies at the team level can often contribute to theorizing at individual and organizational levels of analysis if multi-level theoretical constructs or generalizing the results to other levels of analysis are appropriate. An exciting prospect, then, is that the degradation in performance experienced by the team that transitioned from Edge structure to Hierarchy structure *might serve as motivator to studies of similar structural transformations at alternate levels of analysis.*

c. Performance vs. Learning

Individual and team performance, as well as individual and team learning, represent dependent variable constructs within many scientific disciplines, and factors attributed to explaining variance within these constructs are innumerable. The work presented in the prior chapters explored these constructs at the intersection of structural contingency, information processing and knowledge flows theorizing. Specifically, this work sought to explore the combined influence of information processing structure and knowledge sharing on individual performance, team performance, individual learning and team learning. While the experimentation provided rich results that can inform multiple

research streams, I suggest that a fourth postulate to emerge from my work involves differentiating the influence of structure and contingency on performance and learning. Put simply:

Postulate 4. *The interaction of information flows and knowledge transfer affect performance and learning differently.*

Performance. Within the experimentation, individuals assigned to teams organized with organic information processing structures (i.e., Edge), when supported by knowledge sharing, clearly outperformed similar individuals assigned to other structure-contingency combinations (see Table 40 and Figure 18 for details). At the work group level, teams subjected to Edge information processing structures and supported by knowledge sharing clearly outperformed comparable teams subjected to other structure-contingency combinations (see Table 44 and Figure 20 for details). The interaction of structure and contingency thus enhances both individual and collective performance. These parallel findings are important and one of their implications – i.e., the necessity for information processing structures to be sufficiently robust in order for the exchange of actionable information (e.g., knowledge) to affect objective performance – is discussed earlier in the chapter.

Learning. In contrast, the experimentation suggests that *individual learning is influenced by interaction of information processing structure and knowledge sharing, but team learning is largely indifferent to these combined manipulations*, at least as operationalized during the experimentation. These results are contrary to *Hypothesis 3*, which predicted that Edge teams would learn more quickly than Hierarchy teams. The finding is also contrary to *Hypothesis 5*, which predicted that teams supported with knowledge sharing would learn more quickly than teams not supported with knowledge sharing. The experimental results did hint, however, that sharing explicit knowledge

²³ During the experimentation, one team changed to Hierarchy after playing ELICIT subject to the Edge configuration for two consecutive experimental sessions; one team changed to Edge after playing ELICIT subject to the Hierarchy configuration for two consecutive experimental sessions.

(e.g., the experimental “postcard”) may assist teams to learn how to complete their work more quickly, even if *Hypothesis 5* did not receive strong statistical support.

In some sense, these results are not surprising, given that constructs for team learning do not often involve team structure as viewed through typical dimensions of organizational design (e.g., Edmondson 1999; Ensley et al. 2003; Sarin & McDermott 2003). However, Gibson and Vermeulen (2003, see also Argote 1999; Hernandez 2003) argue persuasively that elements of team design, such as empowerment and support by knowledge management systems, are important predictors of team learning. As Gibson and Vermeulen (2003) note, these elements may be moderated by subgroup strength (i.e., homogeneity of team members’ demography among small groups within the team). Given their findings, one would expect teams supported with knowledge sharing during the experimentation to exhibit higher rates of learning than others, and as a result, one would have expected strong experimental support for *Hypothesis 5*. Similarly, Bontis et al. (2002) argue that misaligned organizational learning stocks and flows result in organizational underperformance, and it is thus surprising that neither Edge nor Hierarchy structures appeared less “aligned” relative to the team learning within the complex, reciprocally interdependent task of identifying details of an impending terrorist attack, contrary to the prediction of *Hypothesis 3*.

It is possible, however, that the laboratory environment as configured and implemented for this set of experiments provided mechanisms for knowledge transfer, but did not provide an adequate setting for organizational learning to occur (i.e., intuiting, interpreting, integrating, institutionalizing; see Crossan et al. 1999; Zietsma et al. 2002). As implemented during this experimentation, knowledge sharing focused primarily on the transfer of *explicit* knowledge about details of the impending terrorist attack from one team member to another. Many scholars posit, however, the transfer of *tacit* knowledge between team members may provide significant advantage for team learning (e.g., Nonaka 1994; Sole & Edmondson 2002; Edmondson et al. 2003; Nissen 2006). This difference – an experimental focus on explicit knowledge transfer versus emphasis by many scholars on the role of tacit knowledge transfer for enhancing collective learning – perhaps helps to explain the unexpected result that neither varying information

processing structure nor varying the knowledge sharing condition significantly influenced team learning. Even more substantial, however, is that when combined with the extant literature, the experimentation suggests that transfer of explicit knowledge (e.g., what Edmondson et al. 2003 label as “learning what”) versus transfer of tacit knowledge (e.g., what Edmondson et al. 2003 label as “learning how”) may affect team learning in very different ways.

Indeed, the extant literature suggests that explicit learning (i.e., “learning what”) can be both swift and useful for achieving immediate performance gains. This type of explicit learning is extremely useful for resolving the task at hand (leading to performance gains) but may display an ephemeral or transient nature. Explicit learning, it is plausible, may result in more temporary performance gains than tacit learning. Tacit learning (i.e., “learning how”), however, occurs more slowly and may result in outsize performance gains compared to explicit learning (Nonaka 1994; Nissen 2006) once sufficient time is allotted by the learning to occur (Nissen 2007b). Thus, the learning curves (e.g., Asher 1956) for tacit and explicit learning may prove quite different, perhaps even overlapping (Nissen 2007b), and each type of learning (i.e., explicit, tacit) may exhibit unique temporal qualities. Moreover, tacit learning – i.e., the transfer of tacit knowledge – may necessitate use of richer media than explicit learning (Daft & Lengel 1984; Daft & Lengel 1986), necessitating use of compound research designs to explore these relationships.

Within the experimental setting, the transfer of explicit knowledge was operationalized via a highly structured, content-rich device (e.g., “postcard”) that enabled team members to share their current assessment of details about the terrorist attack, as well as the level of certainty that the team member subjectively associated with his or her assessment. Due to restrictions on the communications between subjects, the transfer of tacit knowledge – such as how to assess whether a particular piece of information (e.g., “factoid”) was useful – was generally not accessible to the participants during experimentation. Thus while team members could assist each other with learning *what* analysis was recommended, team members had little opportunity to assist each other with learning *how* to improve their analytical skills.

Despite lack of statistical support for the stated hypotheses, the work nonetheless represents a novel attempt at assessing the influence of team information processing structure (i.e., centralization, formalization and vertical differentiation) on team learning, a topic generally explored at the interteam or interorganizational levels of analysis (see Lane & Lubatkin 1998; Gupta & Govindarajan 2000; Bapuji & Crossan 2004) but explored in this work in the form of intrateam learning. Further, the experimentation suggests that more refined relationships regarding how explicit and tacit knowledge transfer intersect with team information processing structures are likely to prove important for understanding antecedents of team learning and is suggested as a topic for future research.

The operationalization of tacit knowledge transfer and learning within the experimental environment described here is left to future studies, but the argument that tacit and explicit knowledge transfer interact *differently* with performance and learning appears sound. In particular, learning involves the process of *transferring knowledge*, which takes *time* and introduces a longitudinal dimension to the relationships between learning, knowledge creation and knowledge transfer. The differences between explicit and implicit learning are consistent with scholarly descriptions of tacit knowledge as “sticky” and observations that tacit knowledge flows are slower than explicit knowledge flows. Yet tacit knowledge flows result in more powerful and lasting performance results (Nonaka 1994; Nissen 2006). Thus, the experimental results, combined with theorizing about the relationship between knowledge and learning, lend support to existing principles of knowledge dynamics. Building on Nissen (2006, see pp. xiv and 13; also informed by Nissen 2007b), I suggest two final postulates intimated by the empirical results and the theoretical lenses informing my model as motivators for future work:

Postulate 5. *Tacit and explicit knowledge transfer influence learning uniquely.*

Postulate 6. *Explicit and tacit learning exhibit distinct tempos and differing performance outcomes over time and in scope.*

4. Empirical Baseline for Research Campaign

Theorizing about organic organizational structures has served as an underlying motivator of field work for decades (Aiken & Hage 1971; Hull & Hage 1982; Covin & Slevin 1989; Damanpour 1991; Pillai & Meindl 1998; Ambrose & Schminke 2003; Lin & Germain 2003). The Edge structure described in this work serves as an instantiation of organic structures from an information processing framework, grounding organic structures within a knowledge-based view of the firm (Grant 1996b). In this sense, the experimentation contributes to a fruitful and extensive stream of research that explores the utility of organic organizational structures relative to a variety of desired outcomes (e.g., innovation, adaptability, performance), but modernized within information processing and knowledge flows perspectives.

Findings from related computational work (Orr & Nissen 2006; Gateau et al. 2007; Nissen 2007a) suggest that Edge structures resemble and perform as a composite of other forms, notably elements of Mintzberg's (1980) Adhocracy, Professional Bureaucracy and Simple Structure archetypes. Specifically, the Edge form capitalizes on structural dimensions of low centralization, low formalization and low vertical differentiation. Through use of human subjects in a laboratory, the work presented here offers an empirical complement to previous and concurrent computational experimentation (Nissen 2005a; Nissen 2005b; Orr & Nissen 2006; Gateau et al. 2007; MacKinnon 2007; Nissen 2007a) and field work (Looney & Nissen 2006) on Edge organizational structures. The laboratory experimentation offers the opportunity to triangulate at the level of data, investigators, methods and perhaps even theoretical lenses (see Denzin 1978 and Jick 1979; for a re-interpretation of triangulation within organizational research, see Cox & Hassard 2005). The experimentation with human subjects outlined here assists with strengthening and refining theory development related to organic organizational structures. The work also serves as an empirical baseline for future experimentation using the ELICIT framework (e.g., Lospinoso & Moxley 2007), serving as a comparative case as alternate manipulations are incorporated into the

experimentation to investigate newly posited research questions. The research thus complements and extends an already generative research stream related to organic organizational structures.

B. SUGGESTIONS FOR FURTHER RESEARCH

In this section, I discuss how my work motivates future research and thus serves as generative inquiry (Gergen 1978). I start with possibilities for extending and conducting further testing of the theoretical model, then discuss other theoretical lenses through which interpretation of the experimental data could prove fruitful.

1. Extend & Test Theoretical Model

One of the primary contributions of this work is a theoretical model that posits that the interaction of information processing structure (i.e., organic, mechanistic) and knowledge sharing (i.e., supported, not supported) influences individual and team performance when teams undertake complex, reciprocally interdependent tasks. The experimentation guided by the model yielded significant results, suggesting that it offers utility for explaining performance. However, extensions to the model are clearly possible, and I discuss some of the possibilities here.

a. Other Types of Task Environments

The task context for the experimentation can be characterized as objectively complex (Frost & Mahoney 1976; Campbell 1988; see also Terborg & Miller 1978; Campbell & Gingrich 1986) and reciprocally interdependent (Thompson 1967). Campbell (1988) identifies a typology of 16 complex task types, which he categorizes into decision, problem, fuzzy or judgment tasks (p. 47). The experimentation presented in this work is most closely aligned with Campbell's category of *problem* tasks, which involve path multiplicity, conflicting interdependence within the paths, and uncertainty. Similarly, Thompson (1967) differentiates between reciprocal, sequential, and pooled interdependence, with reciprocal interdependence characterized by "each unit posing contingency for the other" (p. 55). The task design in the experimentation described here

is reciprocally interdependent. Given these differentiations by Thompson (1967) and Campbell (1988), one straightforward analysis and extension of the model could be ensuring that the findings presented in this work are stable across all task categories and types of interdependence.

Task complexity also serves as an important variable for group decision support systems (e.g., Zigurs & Buckland 1998; Zigurs et al. 1999), so further experimentation using the results reported herein as a baseline could serve to inform that literature. Moreover, as task complexity can be individually defined and socially constructed (e.g., Campbell 1988; Maynard & Hakel 1997), it would perhaps prove worthwhile to consider this model within the context of individual and/or group *perceptions* of task complexity, allowing concepts such as goal setting (e.g., Early et al. 1990) or self-efficacy (e.g., Mangos & Steele-Johnson 2001) to serve as extensions to the theoretical model. Further, task complexity and task type also influence information seeking and retrieval behavior (e.g., Byström & Järvelin, 1995; Vekkari 1999), offering another opportunity for extending the model relative to exploring issues related to task complexity.

b. Other Motivational Constructs

Cacioppe (1999) defines 44 individual-team reward strategies, distinguishing them according to their relationship to extrinsic and intrinsic motivation. The experimentation for this work leveraged incentive structures involving public recognition, praise, feedback, team building and team attention, but it seems plausible that alternate motivational constructs could influence information processing and knowledge sharing behaviors when undertaking complex, reciprocally interdependent tasks. Osterloh and Frey (2000), for example, suggest that intrinsic and extrinsic motivation interact with explicit and tacit knowledge generation and transfer to produce organizational forms, intimating motivation as an endogenous variable of the firm (Osterloh et al. 2002). Relative to the theoretical model motivating this work, motivation could either be incorporated as part of structure (as Osterloh et al. 2002 suggest), or serve as an exogenous influence to the structure construct (e.g., Quigley et al. 2007). The

influence of motivation on individual and team performance is well theorized, and thus another natural extension of the model could include careful consideration of how motivation, information processing structure, and knowledge sharing *interact* to influence performance. Motivation could be incorporated as part of structure or inserted as an exogenous variable.

c. Other Types of Knowledge Transfer

Nonaka (1994) suggests four modes of knowledge conversion, differentiated by the type of knowledge (i.e., tacit, explicit) from and to which the conversion occurs. While the theoretical model motivating the work presented in this dissertation does not specify how the *type* of knowledge conversion (i.e., socialization, internalization, externalization, combination) interacts with information processing structure to affect performance, such nuance would represent a reasonable extension of the work. Close scrutiny of the experimental environment suggests, for example, that while sharing explicit knowledge was supported during the experimentation, sharing tacit knowledge was not generally supported. Yet knowledge sharing clearly influenced individual performance, team performance, and individual learning, implying that the theoretical model offers some utility for explaining variance in individual and team behaviors. Extending the experimental environment such that the transfer of tacit knowledge is incorporated (e.g., *how* to assess the utility of a given piece of information relative to other pieces of information vs. *what* a subject currently assesses as the pertinent details of the terrorist attack) could serve to further evaluate the model's usefulness.

2. Other Theoretical Disciplines

In this section, I discuss how my work could inform related theoretical disciplines and constructs such as metacognition, complex systems, network organizations, military command and control, and an intersection of information theory, information processing theory, and human cognition.

a. Metacognition

Although longstanding within the developmental and cognitive psychology literatures (see Schwartz & Perfect 2002 for a brief discussion), metacognition is a relatively recent concept for team and organizational theorizing. Broadly speaking, team and organizational metacognition refer to knowledge about what others know or might be expected to know within a team or organization (Metcalf & Shimamura 1994). Many scholars posit that metacognition assists with work group performance and learning (e.g., Kilduff et al. 2000; Hinsz 2004; Salas & Fiore 2004). As an example, a metacognitive mapping of a team might indicate which members of a team possess which skills, or perhaps which team members have experience with various types of situations. With this metacognitive mapping of team skills, a team might more adequately match task to team member, and thus provide higher-performing output than a similar team lacking access to its metacognitive map.

McLennann et al. (2006) offer an omnibus definition of team metacognition as the “core team members’ knowledge of the current states and processes of the team in relation to those states and processes required for the team’s goals to be achieved, and their ability to control and modify those team states and processes.” (p. 34) Deconstructed, this definition suggests a view of team metacognition in which some team members are more central than others. Moreover, through sensemaking, these core team members assess the current state of a team and its processes relative to a desired future state. Presumably, the core (i.e., more central) team members intervene with various controls and process modifications to move the team closer toward the desired future state. Looney and Nissen (2006) define collective metacognition more simply, suggesting a definition of organizational metacognition as “knowing what an organization knows.” They posit that enabling organizational metaknowledge networks to become more explicit can assist team performance when undertaking complex tasks.

On a limited scale, the ELICIT environment provides an opportunity to study team metacognition. Within the experimental environment, participants may post information (e.g., “factoids”) on websites; read/write privileges vary according to the

information processing structure to which the participant is assigned. Within Edge information processing structures, subjects select whether to post information to any combination of the four websites (e.g., subjects may post the factoid to one, any two, any three, or all four websites). This protocol enables the subjects, in a limited fashion, to metatag the information as being *most* relevant to one aspect of the impending attack – such as who is responsible, or where the attack will occur – if the subjects so desire. The opportunity to metatag the information in this manner is not available to participants assigned to Hierarchy information processing structures; those subjects have access to only the website for which their team is responsible (i.e., who, what, where or when). As a result, team members within Hierarchies have only one choice as for posting or retrieving information from a website.

If we think of the websites as a device in which organizational metacognition can be stored (e.g., a piece of information is relevant to determining who is responsible for the attack is posted only on the who website, but not the where website), the experimental setting, as currently configured, offers an opportunity to explore the influence of metacognition on team performance. Additionally, the experiment's knowledge sharing device (e.g., postcard) can also serve with explorations of metacognition, as the receiver of the postcard gains an explicit understanding of the sender's mental model of the impending terrorist attack. Given 1) the recency with which team and organizational metacognition have entered the academic discourse and 2) primary emphasis in scholarly work on how to elicit existing metacognition vice assessing the influence of metacognition on other outcomes (e.g., Carley 1997; Cooke et al. 2000; Mohammed & Dunville 2001; Cooke et al. 2004), the experimental environment thus provides an intriguing means of exploring how organizational metacognition interacts with a complex, interdependent task environment to influence individual and collective performance.

b. Complex Systems

Organizations have been described as complex systems (Galbraith 1973; Perrow 1984; Scott 2003; Curşeu 2006), leading some researchers to study organizations

(and organizational change) through a lens of complex adaptive systems (Dooley 1997; MacIntosh & MacLean 1999; Salem 1999). Studies of organizations in the complex systems framework often view organizational relationships through an information processing lens (Dooley 1997; Scott 2003). In a complex systems view, Edge and Hierarchy represent neither organizations nor teams, but rather *states* that the complex system could realize. Modifications to the ELICIT software could allow the experimenter to design *other states* – or perhaps even *transition processes from one state to another* – for empirical investigation. Explicit control enables the researcher to investigate system states that may be unstable or temporary, and thus elusive, within field studies.

For example, Edge and Hierarchy can be characterized as temporarily stable states of a complex information processing system. Similarly, the structural transformation between Edge and Hierarchy discussed in this work can be interpreted as points of system bifurcation (e.g., Black & Edwards 2000). Given the high level of instrumentation provided in the ELICIT environment, it seems highly plausible to study emergent behavior of other organizational “states” using the work presented here as a baseline. Researchers could operationalize important characteristics (e.g., stability) of the “states” of human organizing within the environment, then design appropriate manipulations to explore the theoretical constructs suggested by them. For example, such studies could contribute to the important work of translating the latent construct of dynamic complexity (Sterman 2001)—often characterized along dimensions such as nonlinear dynamics, self-organizing, and feedback—into operationalized constructs within ELICIT for experimental investigation. Similarly, such investigations could also serve the useful purpose of operationalizing translations of various concepts within chaos theory to the organizational domain (e.g., Thiétart & Forgues 1995).

Of course, much theoretical work remains to link systems theory with organizational theory. However, through viewing Edge and Hierarchy as instantiations of states within a larger complex system of human organizing, these empirically grounded linkages offer a means to explore the intersection of complex systems and human organizing in less abstract yet potentially generative way. The findings herein

could serve as an experimentally-grounded complement to existing theorizing at the intersection of complex systems and organizational design (e.g., Perrow 1984; Dooley 1997; Curşeu 2006), assisting with theory refinement.

c. Network Organizations

Drawing from chaos and complexity theory, Black and Edwards (2000) suggest that network organizations, a term they interchange freely with virtual organizations, are an “outgrowth of the change in dominant logic in the operations of current markets in the information age.” (p. 574) Borgatti and Foster (2003) argue that the ontological status of the network organization is less clear, positing instead that network organizations do not necessarily refer to an organizational structure with specific properties that enable comparison against other archetypal forms. Rather, they argue that network organizing serves as an omnibus paradigm for thinking about relationships between organizational actors, and moreover, that the links between these actors can represent different types of relationships at levels of analysis ranging from intragroup to interorganizational. Suggesting that network organizations emerged as post-bureaucratic forms of organizing, Miles and Snow (1992) describe three types of network organizations—stable, internal and dynamic—that are differentiated by operating logic (i.e., resource allocation mechanisms) and primary application (i.e., task environment and industry type). Similarly, Achrol (1996) identifies four types of interorganizational networks—the internal market, the vertical market, the intermarket and the opportunity network. Other organizational scholars suggest that regionally-based or functionally-based interfirm consortia (e.g., Hanssen-Bauer & Snow 1996) serve as exemplars of network organizations. Monge and Contractor (2003) draw from communication theory to suggest that patterns of communication among various organizational agents serve as primary units of analysis for network organizing, and Wasserman & Faust (1994), grounding their work in graph theory, suggest that nearly any type of node-link-node relationship serves as fodder for network analysis. Van Alstyne (2002) finds that the concept of network organizations is cross-disciplinary, spanning computer science, economics, and sociology.

This cursory review suggests that the concept of network organizations, while intuitively appealing, invokes distinctive but overlapping meaning systems throughout a variegated set of literatures, making its theoretical operationalization tentative. Throughout literatures that incorporate the network organization concept, however, scholars seem to consistently echo how increasing uncertainty, highly dynamic environments, globalization, and new communication technologies are changing the organizational landscape to one in which flatter, leaner, and more flexible organizations make decisions more rapidly than in the past (see Symon 2000). Network organization thus serves more as a paradigm than an operationalized construct ripe for empirical investigation (see Borgatti & Foster 2003). However, to the extent that network organizations are theoretically equivalent to organic organizational structures (such as emphasis on lateral communications, low centralization, and low formalization), Edge information processing structures can serve as a proxy for comparing network organizations to other archetypal forms. Edge information processing structures, for example, appear to share commonality with all-channel graphs (Mackenzie 1966; Arquilla & Ronfeldt 2001), a specialized type of network in which network density (i.e., the probability that agents within a network communicate) is quite high (see Wasserman & Faust 1994; Scott 2000 for compendia of network measures). The work described here thus provides an opportunity to leverage the controls inherent to laboratory experimentation to complement existing field work (e.g., Tichy & Fombrun 1979; Courtright et al. 1989) on network forms of organization.

d. Military Command and Control in the Postindustrial Age

The experimentation as reported in this work could conceivably offer insight into the design of military command and control processes, and deserves further experimental scrutiny as well as careful consideration by policymakers. Consider, as an example, disaster relief operations. For those at or first to arrive on the scene of a disaster, rescue and relief efforts are often characterized as chaotic, uncertain, and complex. Previous and concurrent computational modeling suggests Edge configurations are preferable in such contexts (Orr & Nissen 2006; Gateau et al. 2007). During relief

operations, stakeholders surface to make demands on already stretched resources, while service providers arrive and attempt to integrate their capabilities into ongoing rescue/relief efforts (Suparamaniam & Dekker 2003; Majchrzak et al. 2007; Waymer & Heath 2007). Although military organizations have long been involved in disaster relief efforts (Anderson 1970; Shubert 2004; Bello 2006), few, if any, laboratory experiments have informed senior defense officials about the types of command and control structures that may prove most useful for integrating military capabilities into relief efforts.

While preliminary, my empirical investigations suggest that given overarching goal clarity, military units assigned to disaster relief missions and vested with Edge-like characteristics could outperform similar military units assigned to disaster relief missions and managed via a more traditional Hierarchy command and control structure. Certainly, this assertion is broad and sweeping, and instantiation of Edge-like command and control processes versus Hierarchical command and control processes for military units requires further reflection and discourse that might prove fruitful. At an abstract, basic level, however, the experimental findings suggest that nontraditional thinking about military command and control processes may be a useful step toward designing high-performance organizations for complex, chaotic environments.²⁴

e. Information Theory and Cognitive Information Processing

Shannon's (1948a, 1948b) information theory includes a basic sender-receiver model for information transfer, providing a framework for decades of research on noise and attenuation during transmission of communications. Miller (1956) extends Shannon's model to human cognition, and given Miller's framework and others that follow, it is clear that noise, ambiguity, deception, and related topics within information processing influence individual and team cognition. As currently configured, the ELICIT experimental environment is well instrumented to observe micro-level individual

²⁴ Anecdotal evidence suggests that some U.S. military organizations are embracing Edge-like organizing in various contexts, such as Strategic Command's widespread use of blogs that differentiate command (e.g., control) relationships from information relationships, use of blogs and wikis within the U.S. intelligence community (Rogin 2007), and emerging concepts such as network-centric warfare and reachback that result in flattened organizational structures during tactical operations (e.g., Neal 2000; Lackey 2003; Newman 2003).

information processing behaviors relative to a complex task, as well as the interactions that individuals working within the environment initiate with others (e.g., send, receive, seek, share). Metadata about individual information processing behaviors are recorded to the nearest second in text files. These text files are then available for comparative analysis against experiments performed under alternate conditions and/or types of subjects. In this vein, the data collected during this experimentation could serve as a baseline for future work in which new manipulations are introduced into the experimental environment.

In the tradition of seminal studies on patterns of communication (e.g., Bavelas 1950; Leavitt 1951) and drawing from the cognition and information theory literatures, it could be fairly straightforward to motivate a number of more contemporary studies to examine cognition, performance and team dynamics for testing within the ELICIT environment. Motivated theoretical constructs could be operationalized through minor adaptations of the current experimental configuration. For example, information processing behaviors and resultant performance could be compared relative to conditions of low levels of irrelevant information (i.e., “noise”) versus high levels of irrelevant information. In the experiments outlined in this work, the ratio of relevant to all data was approximately fifty percent, and as such the data could serve as mid-range baseline case.

Likewise, deceptive information could be introduced into the experiment to consider its effects on individual and group cognition, information processing, and performance. In a similar vein, the information inputs could be modified to require more sophisticated problemsolving, such as through adding greater ambiguity or uncertainty to the task. Alternately, the symbolic complexity of the problem solution could be manipulated for experimentation, as well as the complexity of the task. All of these extensions are straightforward to implement, and relate directly to information theory (Shannon 1948a; Shannon 1948b), information processing theory (Galbraith 1974), and an information processing view of human cognition (Miller 1956).

C. SUMMARY

In this work, I first characterized and then explored the intersection of structural contingency, information processing, and knowledge flows theorizing, focusing on teams as my primary level of analysis. I suggested that little is known about how this theoretical intersection affects collective performance. Drawing upon the rich history of structural contingency theory (e.g., Woodward 1965; Lawrence & Lorsch 1967a, 1967b) and its recent explicit extension into team level analysis (e.g., Hollenbeck et al. 2002), I used this framework to organize my thinking about what information processing and knowledge flows theories mean for teams, and particularly, team performance.

Like structural contingency theory, information processing theory (e.g., Thompson 1967; Galbraith 1974) and knowledge flows theory (e.g. Nonaka 1994; Nissen 2006) are well established in their own right. My work is thus more integrative than novel, consistent with study inside a discipline – information sciences – that in many ways is still constructing the corpus of its theoretical ancestry (e.g., Shannon 1948a, 1948b; Bavelas 1950; Leavitt 1951; Miller 1956; March & Simon 1958; Lawrence & Lorsch 1967a; Borko 1968; Simon 1973; March 1991; Monge & Contractor 2003) while nonetheless breaking new and exciting ground about the role of information and knowledge within human organizing (e.g., Saracevic 1992, 1999; Orlikowski & Barley 2001). Thus, part of my contribution is offering a cogent synthesis of three research traditions informed by decades of theorizing and empirical studies, and reflecting and embedding a portion of this synthesis into a theoretical model that is compact, integrative, and ripe for empirical investigation. I ground this model within the knowledge-based view of the firm (Grant 1996b), which emphasizes coordination of work and information processing over cooperation of units and/or authority/power dynamics as its primary motivational problem.

Using a computer-mediated experimental environment that offered exceptional instrumentation for recording micro-level behaviors, I tested nine hypotheses motivated at the theoretical intersection described above. Data were collected during a series of experiments with four teams meeting four times over the course of 36 days. Teams were

assigned a similarly complex and reciprocally interdependent task during each experimental session, and I manipulated the information processing structure and knowledge sharing condition to which the teams were subjected in a counterbalanced research design. As my model posits that knowledge sharing *moderates* the influence of team information processing structures on performance, I examined both main and interaction effects suggested by my experimental data. The results were significant and support my assertions that the *interaction* of information processing structure and knowledge sharing affect individual performance, individual learning, and team performance. Results were not significant for how information processing structure and knowledge sharing influence team learning.

From this experimentation and related extant literatures, I derived six postulates that I contend directly motivate future work. These postulates serve as important extensions to how we think about the intersection of team structures and knowledge transfer, particularly viewed through an information processing framework for organizational relationships. Empirical support for my theoretical model also implies that broadening the model to reflect the complexity of modern organizing would likely prove beneficial and illuminating to ongoing discourse about the role of information and knowledge within contemporary work. Moreover, interpretation of the experiment's operationalizations via alternate theoretical lenses – from metacognition and complex systems theory to military command and control – offers reasonable evidence that the work represents generative inquiry (Gergen 1978) for the academic community across multiple theoretical traditions while simultaneously offering benefit to practitioners.

My work, then, should offer appeal to both researchers and practitioners. For the academy, the introduction of my theoretical model offers a means to integrate three distinct but overlapping theoretical traditions in a coherent manner. Additionally, the results from my experimentation should be of interest to those who study teams and work groups, particularly when grounded in knowledge-based views of the firm. For practitioners, my experimentation suggests that information flows and knowledge sharing are integrally linked. This linkage implies that for teams to improve when undertaking

complex tasks, investing in improved information flows probably must be balanced against investments in team knowledge creation in order to achieve expected performance gains.

Clearly, however, more work remains. I am hopeful that the model, results, and postulates presented here can serve as motivation for future work, as the theoretical intersection I explored is clearly useful for explaining collective performance.

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APPENDIX A: INSTITUTIONAL REVIEW BOARD

A. APPROVAL (18 JAN 2007)



Naval Postgraduate School Institutional Review Board (IRB)

18-Jan -07

From: LT Brent Olde, Ph.D.
To: Associate Professor Mark E. Nissen
Subject: YOUR PROJECT: DECISION MAKING IN HIERARCHAL AND
EDGE ORGANIZATIONS

1. The NPS IRB is pleased to inform you that the NPS Institutional Review Board has approved your project (NPS IRB# NPS20070030).
2. The NPS IRB was originally certified by BUMED on 26 July 2002 and has been re-certified until 30 March 2007.
3. This approval is valid for one year from this date. Please submit a copy of all records and consent forms to the Research and Sponsored Programs Office (Laura Ann Small, Halligan Hall, Room 201B) at the conclusion of this project.
4. If your protocol changes at any time, you will need to resubmit your project proposal to the NPS IRB.

Sincerely,

A handwritten signature in black ink, appearing to be 'B. Olde'.

Lt Brent Olde, Ph.D.
Chair
NPS Institutional Review Board

B. APPLICATION (ELECTRONICALLY SIGNED AND SUBMITTED 27 DEC 2006)



Mark E. Nissen, Ph.D.
Information Sciences Department
238 Root Hall
Naval Postgraduate School
Monterey, California 93943

831-656-3570
DSN: 756-3570
MNissen@nps.edu

To: Protection of Human Subjects Committee

Subject: Application for Human Subjects Review (Title): Decision Making in Hierarchal and Edge Organizations

1. Attached is a set of documents outlining a proposed experiment to be conducted over the next year for our OSD sponsored project and Information Sciences doctoral studies.
2. We are requesting approval of the described experimental protocol. An experimental outline is included for your reference that describes the methods and measures we plan to use.
3. We include the consent forms, privacy act statements, all materials and forms that a subject will read or fill-out, and the debriefing forms (if applicable) we will be using in the experiment.
4. We understand that any modifications to the protocol or instruments/measures will require submission of updated IRB paperwork and possible re-review. Similarly, we understand that any untoward event or injury that involves a research participant will be reported immediately to the IRB Chair and NPS Dean of Research.

Mark E. Nissen

APPLICATION FOR HUMAN SUBJECTS REVIEW (HSR)	HSR NUMBER <i>(to be assigned)</i>
PRINCIPAL INVESTIGATOR(S) <i>(Full Name, Code, Telephone)</i> Nissen, Mark E., 06/IS, 656 3570	
APPROVAL REQUESTED <input checked="" type="checkbox"/> New <input type="checkbox"/> Renewal	
LEVEL OF RISK <input type="checkbox"/> Exempt <input checked="" type="checkbox"/> Minimal <input type="checkbox"/> More than Minimal Justification: Subjects participate in analysis and decisionmaking activities similar to those performed by intelligence analysts throughout the Department of Defense. The experimental setting is a standard office environment using a Windows PC software tool. The pre- and post-experimental survey instruments are well accepted in their fields, with prior use on hundreds of subjects with no known adverse affects. This activity meets the definition of minimal risk outlined in 45 CFR 46.102(h)(i) , which states: "Minimal risk means that the probability and magnitude of harm or discomfort anticipated in the research are not greater in and of themselves than those ordinarily encountered in daily life or during the performance of routine physical or psychological examinations or tests."	
WORK WILL BE DONE IN (Site/Bldg/Rm) Root & Ingersoll Hall Computer Labs and Classrooms	ESTIMATED NUMBER OF DAYS TO COMPLETE 365
MAXIMUM NUMBER OF SUBJECTS 136	ESTIMATED LENGTH OF EACH SUBJECT'S PARTICIPATION 4 x 90 minutes per subject + 30 minutes pre-testing
SPECIAL POPULATIONS THAT WILL BE USED AS SUBJECTS <input type="checkbox"/> Subordinates <input type="checkbox"/> Minors <input checked="" type="checkbox"/> NPS Students <input type="checkbox"/> Special Needs (e.g. Pregnant women) Specify safeguards to avoid undue influence and protect subject's rights: Participation in the experiment is fully voluntary. Student subjects who participate in the experiment are part of the Information Sciences doctoral program, as well as the Command, Control, Computers, Communications and Intelligence (C4I) curriculum. The experiment relates directly to their courses of study, as it investigates organization, communication and decisionmaking performance within the typical DoD activity of counterterrorism analysis. Students whom elect not to participate will be provided with alternate assignments to meet learning objectives.	

<p>OUTSIDE COOPERATING INVESTIGATORS AND AGENCIES</p> <p>n/a</p> <p><input type="checkbox"/> A copy of the cooperating institution's HSR decision is attached.</p>
<p>TITLE OF EXPERIMENT AND DESCRIPTION OF RESEARCH</p> <p>“Exploring Patterns of Communication, Decision Making and Mental Models in Hierarchal and Edge Organizations”</p> <p>This experiment explores the influence of organizational form on team patterns of communication, development and exchange of mental models, and decision-making performance. Using the ELICIT software developed for OASD-NII, seventeen participants are tasked with combining 68 factoids in order to uncover the “who, what, where and when” of a fictitious terrorist plot, to include fictitious geolocations (e.g. “Alphaland”) and characters. The type of reasoning requested of the subjects is analogous to playing the popular board game <i>Clue</i>. During each experimental round, participants can share factoids via the ELICIT software, post the factoids to intranet websites on the ELICIT server, and send written assessments of the threat to each other via the proctors. Subjects will be asked to complete a personality profile (i.e., NEO-FFI) prior to undertaking the experiment, and to complete a trust/advice network survey upon completion of each experimental round. The personality, trust, and advice surveys are well-established instruments from their respective fields, used on hundreds of subjects with no known adverse effects. All individual results will be held in confidence. Each round of experimentation, to include post-experiment surveys, is estimated to require a maximum of 90 minutes of participant time, with no more than 4 rounds per subject over the course of a calendar month. The ELICIT software executes in a standard Windows PC environment common across the DoD enterprise. The experiment will be executed in a standard office environment familiar to the subjects.</p>
<p>I have read and understand NPS Notice on the Protection of Human Subjects. If there are any changes in any of the above information or any changes to the attached Protocol, Consent Form, or Debriefing Statement, I will suspend the experiment until I obtain new Committee approval.</p> <p>SIGNATURE_____ DATE_____</p>

Naval Postgraduate School

Participant Consent Form & Minimal Risk Statement

Introduction. You are invited to participate in a study entitled Team Decision Making being conducted by the Naval Postgraduate School Information Sciences Department.

Procedures. If I agree to participate in this study, I understand I will be provided with an explanation of the purposes of the research, a description of the procedures to be used, identification of any experimental procedures, and the expected duration of my participation. Synopsis: There will be five in-class sessions and one at-home exercise. The in-class sessions include: (1) 30 minute pretest phase, (2) four 90 minute execution phases, during which you will be asked to be part of a decision-making team under varying organizational conditions, and (3) a take home written assignment of 2-5 pages, in which you will be asked to discuss the pros and cons of each organizational form you experience, as well as your thoughts about how your decision-making and team performance was affected during each experimental round.

Risks and Benefits. I understand that this project does not involve greater than minimal risk, and that it involves no known, reasonably foreseeable risks or hazards greater than those encountered in everyday life. I have also been informed of any benefits to myself or to others that may reasonably be expected as a result of this research.

Compensation. I understand that no tangible reward will be given. However, active participation in this experiment represents a deliberate aspect of my coursework, and I expect to perform to the best of my ability in all experimental sessions. I understand that a copy of the research results will be available at the conclusion of the experiment.

Confidentiality & Privacy Act. I understand that all records of this study will be kept confidential, and that my privacy will be safeguarded. No information will be publicly accessible which could identify me as a participant, and I will be identified only as a code number on all research forms. I understand that records of my participation will be maintained by NPS for five years, after which they will be destroyed.

Voluntary Nature of the Study. I understand that my participation is strictly voluntary, and if I agree to participate, I am free to withdraw at any time without prejudice.

Points of Contact. I understand that if I have any questions or comments regarding this project upon the completion of my participation, I should contact the Principal Investigator, Dr. Mark Nissen, 656-3750, MNissen@nps.edu. Any medical questions should be addressed to LTC Eric Morgan, MC, USA, (CO, POM Medical Clinic), (831) 242-7550, eric.morgan@nw.amedd.army.mil.

Statement of Consent. I have read and understand the above information. I have asked all questions and have had my questions answered. I agree to participate in this study. I will be provided with a copy of this form for my records.

Participant's Signature

Date

Researcher's Signature

Date

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APPENDIX B: SAMPLE INSTRUCTIONS TO PLAYERS

Instructions (Edge)

You have been assigned to an Edge organization. Your goal is to identify details about an impending terrorist attack. You may communicate to other players in two ways: 1) sharing and posting factoids via the software posting factoids to websites, and 2) sending “postcards.” You may also pull factoids from websites. Verbal communication is not permitted during the game.

Edge organization

Edge organizations are generally described as decentralized (i.e., decisionmaking is distributed across the organization) and less formalized (i.e., possessing few rules, procedures, and paperwork) than more traditional, bureaucratic organizations. Communication is often frequent. Members of edge organizations tend to coordinate their work through informal communication among highly knowledgeable peers.

Sharing, posting and pulling factoids via the software

The software supports two ways of informing group members about factoids you have “discovered.” You can **Share** a factoid directly with another group member using the Share tab. You can also **Post** a factoid to or **Pull** a factoid from any website. Other group members can do the same.

There are four websites: Who, What, Where and When. Though these areas are called websites, the information display is provided by the experiment software and not by the Internet.

- Factoids in your inbox can be copied into your MyFactoids list by selecting the factoid and clicking on the **Add to MyFactoids** action.
- To **Share** a factoid, select the factoid from either your inbox or your MyFactoids list that you wish to share. Click on the **Share** action, and select the pseudonym of the person with whom you want to share. This sends the factoid to the selected player’s inbox message list.
- To **Post** a factoid, select the factoid from your inbox or MyFactoids list. Click on the **Post** action, and select the website you wish to post to.
- To **Pull** a factoid, select the factoid you wish to copy from the website and click on the Add to MyFactoids action. The **Add to My Factoids** action can be used to copy a factoid from a website to your MyFactoids list.

Sending “Postcards”

Periodically during the experiment, you will be asked to send a “postcard” to one other player of your choosing. You do NOT have to send the postcards to the same player each time. The postcard should reflect your assessment of the attack details at that point in time. Your postcards must have the following format:

Postcard				
From: <your pseudonym>		Date:		
To: <addressee's pseudonym>		Time:		
My assessment of the attack is:		Certainty		
Group: _____	High	Moderate	Low	None
Target: _____	High	Moderate	Low	None
Country: _____	High	Moderate	Low	None
Month: _____	High	Moderate	Low	None
Day: _____	High	Moderate	Low	None
Time of day: _____	High	Moderate	Low	None
Method of attack: _____	High	Moderate	Low	None

Other software tools

Some other tools are available to you in the software:

- a) • To get a summary list of all the factoids in your MyFactoids list, click on the MyFactoids tab in the middle of your screen.
- b) • To find out your role information and how other members of your group see you, click on the “How I’m seen” tab.
- c) • To get a list of all the members in your group, with information about their role and country, click on the “What I see” tab.
- d) • To access information from a team website, click on the website that you wish to view. To update the website with the latest information that has been posted to it, click on the Refresh action at the top of the screen, while viewing the website.

Identifying the Who, What, Where, and When of the Attack

When you think that you have identified the who, what, where and when of the adversary attack, click on the **Identify** tab at the top of your screen and enter free text messages that identify the who, what, where and when of an adversary attack. **Partial answers are accepted, but you may Identify only one time.**

- The who is a group (for example the blue group).
- The what is a type of target (for example an embassy or religious school or dignitary)
- The where is the country in which the attack will take place (for example Alphaland)
- The when is the month, day and time of day on which the attack will occur (for example December 15, at 3:00 a.m.)

During the game

During each experiment round, you are free to work on any aspect of the task.

Winning the Game

Once all the players have identified a solution and the surveys are complete, you will be asked to determine who emerged as the ‘team leader’ during this round. Your selection should reflect a group consensus. After the game has been played, you may talk amongst each other to select the emergent team leader. Verbal

communication is not permitted during the game, but is permitted once all of the surveys are complete and you are selecting your emergent team leader.

The games are structured as a tournament that recognizes the contributions of both individuals and groups. You receive one individual point **if you identify the correct solution and your emergent group leader identifies the correct solution**. Your group receives a group point if your emergent **group leader identifies the correct solution**. After the four games are played, the points will be totaled. You can receive a maximum of four individual points during the tournament, and your group can receive a maximum of four group points. In the event of an individual tie (e.g., 11 players identify four correct solutions and the emergent group leader identifies the correct solution in all cases), the fastest individual average time to identify wins. In the event of a group tie (e.g., all group leaders identify the correct solution), the fastest average time for the group to identify will win. **Therefore, it is in your best interest to identify the correct solution as quickly as possible while also ensuring that your emergent group leader identifies the correct solution as quickly as possible.** You may only use the 'identify' function in the software one time.

Game Over

The game is over when all players have made their identification, or 60 minutes have elapsed (whichever is sooner). You will also be asked to complete a different short survey at the end of the experiment.

Summary

You have been assigned to an edge organization. This assignment affects how you can communicate with other players.

- Sharing factoids: You may share factoids with any player of your choosing, and you may share any single factoid as many times as you wish. Factoids are shared via the ELICIT software.
- Sending postcards: You may send a postcard to any player of your choosing at specified intervals.
- Posting to websites: You can post any factoid to any website of your choosing.
- Pulling from websites: You may pull factoids posted on any website.

When you have finished reading this important background information and are ready to begin, click the Ready button in the upper left corner of your screen.

Thank you for playing, and good luck!

Edge

I want to:

Share a Factoid	Factoids can be sent to any other player via the software
Send a Postcard	Handwritten postcards can be sent to any other player
Post a factoid to a website	Factoids can be posted to any website via the software
Pull a factoid from a website	Factoids can be pulled from any website via the software

Note 1: Instructions were adapted from prior experimentation (see Parity 2006).

Instructions (Hierarchy)

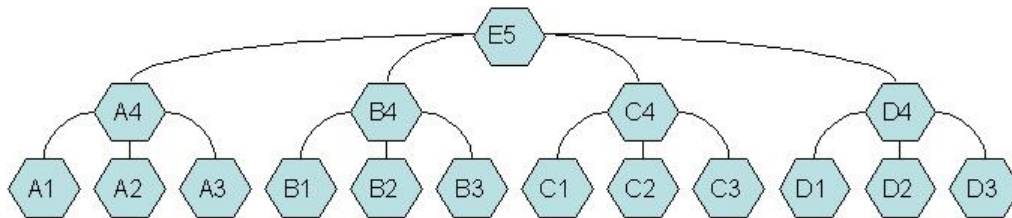
You have been assigned to a Hierarchy organization. Your goal is to identify details about an impending terrorist attack. You may communicate to other players in two ways: 1) sharing and posting factoids via the software posting factoids to websites, and 2) sending “postcards.” You may also pull factoids from your team’s website. Verbal communication is not permitted during the game.

Hierarchy organization

Hierarchy organizations are generally described as centralized (i.e., decisionmaking is retained by higher-level management) and formalized (i.e., possessing many rules, procedures and paperwork).

Communication can be less frequent than other types of organizations. Members of hierarchal organizations tend to specialize in particular functional areas, accomplishing their work according to established standards, rules and procedures.

There are four teams of four members each plus an overall cross-team coordinator. The four teams are organized according to a traditional hierarchical structure, each with a leader. The diagram shows the relationship between a cross-team coordinator (E5), the four leaders (A4, B4, C4 and D4), and their team members:



Team A is focused on who, team B on what, team C on where and team D on when. The overall coordinator coordinates information between the team leaders across team boundaries. Note that the above diagram is an organization chart and not a communications chart. Additional lateral communications capabilities are available to enable you to share information with any member of your team. Note: In these instructions, group refers to all 17 players. Team refers to members assigned to teams A, B, C or D.

Sharing, posting and pulling factoids via the software

The software supports two ways of informing team members about factoids you have “discovered.” You can **Share** a factoid directly with any group member using the Share tab. You can also **Post** a factoid to or **Pull** a factoid from your team’s website. Your team members can see the factoids and post their factoids to your team’s website. For example, all members of the “where” team can see items posted to their team’s “where” website. The cross-team coordinator can see all four of the websites.

Each of the four teams in your group has its own website. Though these areas are called websites, the information display is provided by the experiment software and not by the Internet.

- Factoids in your inbox can be copied into your MyFactoids list by selecting the factoid and clicking on the **Add to MyFactoids** action.
- To **Share** a factoid, select the factoid from either your inbox or your MyFactoids list that you wish to share. Click on the **Share** action, and select the pseudonym of the person with whom you want to share. This sends the factoid to the selected player’s inbox message list.
- To **Post** a factoid, select the factoid from your inbox or MyFactoids list. Click on the **Post** action, and select your team’s website.

- To **Pull** a factoid, select the factoid you wish to copy from your team's website and click on the Add to MyFactoids action. The **Add to My Factoids** action can be used to copy a factoid from a website to your MyFactoids list.

Sending "Postcards"

Periodically during the experiment, you will be asked to send a "postcard" to your team leader or a peer within your team. Each of the team leaders will send his or her postcard to the cross-team leader or to a member of his or her team. The cross-team leader will send his or her postcard to ONE of the team leaders. The postcard should reflect your assessment of the attack details at that point in time. Your postcards must have the following format:

Postcard					
From: <your pseudonym>	Date:				
To: <addressee's pseudonym>	Time:				
My assessment of the attack is:					
Group: _____	High	Moderate	Low	Certainty None	
Target: _____	High	Moderate	Low	None	
Country: _____	High	Moderate	Low	None	
Month: _____	High	Moderate	Low	None	
Day: _____	High	Moderate	Low	None	
Time of day: _____	High	Moderate	Low	None	
Method of attack: _____	High	Moderate	Low	None	

Other software tools

Some other tools are available to you in the software:

- To get a summary list of all the factoids in your MyFactoids list, click on the MyFactoids tab in the middle of your screen.
- To find out your role information and how other members of your group see you, click on the "How I'm seen" tab.
- To get a list of all the members in your group, with information about their role and country, click on the "What I see" tab.
- To access information from your team website, click on the website that you wish to view. To update the website with the latest information that has been posted to it, click on the Refresh action at the top of the screen, while viewing the website.

Identifying the Who, What, Where, and When of the Attack

When you think that you have identified the who, what, where and when of the adversary attack, click on the Identify tab at the top of your screen and enter free text messages that identify the who, what, where and when of an adversary attack. Partial answers are accepted, but you may identify only one time.

- The who is a group (for example the blue group).
- The what is a type of target (for example an embassy or religious school or dignitary.)
- The where is the country in which the attack will take place (for example Alphaland.)
- The when is the month, day and time of day on which the attack will occur (for example December 15, at 3:00 am.)

During the game

During each experiment round, you are free to work on any aspect of the task.

Winning the Game

The games are structured as a tournament that recognizes the contributions of both individuals and groups. You receive one individual point **if you identify the correct solution and your group leader identifies the correct solution**. Your group receives a group point if your **group leader identifies the correct solution**. After the four games are played, the points will be totaled. You can receive a maximum of four individual points over the tournament, and your group can receive a maximum of four group points. In the event of a tie (e.g., 11 players identify four correct solutions and the group leader identifies the correct solution in all cases), the fastest individual average time to identify wins. In the event of a group tie (e.g., all group leaders identify the correct solution), the fastest average time for the group to identify will win. **Therefore, it is in your best interest to identify the correct solution as quickly as possible while also ensuring that your group leader identifies the correct solution as quickly as possible.** You may only use the 'identify' function in the software one time.

Game Over

The game is over when all players have made their identification, or 60 minutes have elapsed (whichever is sooner). You will also be asked to complete a different short survey at the end of the experiment.

Summary

You have been assigned to a hierarchy. This assignment affects how you can communicate with other players.

- Sharing factoids: You may share factoids with any player of your choosing, and you may share any single factoid as many times as you wish. Factoids are shared via the ELICIT software.
- Sending postcards: You may send postcards to your boss or to your teammates. You may not send postcards to any other player.
- Posting to websites: You may post a factoid only to your team's website.
- Pulling from websites: You may pull a factoid from only your team's website.

When you have finished reading this important background information and are ready to begin, click the Ready button in the upper left corner of your screen.

Thank you for playing, and good luck!

Hierarchy

I want to:

Share a factoid	Factoids can be sent to any other player via the software
Send a postcard	Postcards can be sent only to your boss or a member of your team. If you are the cross-team leader, you may send the postcard to ONE of your subordinates
Post a factoid to a website	Factoids can be posted only to your team's website
Pull a factoid from my team's website or another website	You can pull any factoid from your team's website

APPENDIX C: OPERATIONALIZATION OF ACCURACY

	Correct answer	Subject 1 identification	Accuracy (points)	Subject 2 identification	Accuracy (points)
Who (Group)	Tan	Tan or Blue	0	Tan	1
What (Target)	Omegaland's chancery	Chancery	0	Chancery of Omegaland	1
Where (Country)	Betaland	Omegaland	0	Betaland	1
When (Month)	June	June	1	May or June	0
(Date)	15	15	1		0
(Time)	3 p.m.	1500	1	3	0
	Normalized Accuracy measure		$A = \frac{0+0+0+\frac{(1+1+1)}{3}}{4} = 0.25$		$A = \frac{1+1+1+\frac{(0+0+0)}{3}}{4} = 0.75$

Table 48. Illustration of Accuracy Measurement (Strict Criteria)

	Correct answer	Subject 1 identification	Accuracy (points)	Subject 2 identification	Accuracy (points)
Who (Group)	Tan	Tan or Blue	0	Tan	1
What (Target)	Omegaland's chancery	Chancery	1	Chancery of Omegaland	1
Where (Country)	Betaland	Omegaland	0	Betaland	1
When (Month)	June	June	1	May or June	0
(Date)	15	15	1		0
(Time)	3 p.m.	1500	1	3	0
	Normalized Accuracy measure		$A = \frac{0+1+0+\frac{(1+1+1)}{3}}{4} = 0.50$		$A = \frac{1+1+1+\frac{(0+0+0)}{3}}{4} = 0.75$

Table 49. Illustration of Accuracy Measurement (Relaxed Criteria)

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APPENDIX D: AUTOCORRELATION

In this section, I discuss whether autocorrelation is an issue of concern within the experimental data.

A. AUTOCORRELATION

Analysis of time-series data experimentation has the possibility of introducing autocorrelation effects, which can create inefficiencies in estimation procedures such as least-squares regression (Frank 1971 p. 274). Put simply, autocorrelation refers to the correlation of two values of the same variable X at unique points in time. More specifically, autocorrelation refers to the correlation of X_i and X_{i+k} , where k represents the *lag* in time between measurements of variable X (see Box & Jenkins 1976; Brockwell & Davis 1991). Various techniques exist for mitigating the influence of inefficiencies of estimations produced through analyses of time-series data (see Box & Jenkins 1976; Brockwell & Davis 1991).

B. EXPERIMENTATION

Within the experimentation discussed in the preceding chapters, the primary source of potential autocorrelation stems from subjects playing the ELICIT game multiple times, despite changes to the factoid set during each play of the game. Repeat use of subjects in the research design was purposeful, as the motivated hypotheses included predictions related to individual and team learning (see summary of Chapter II for a reiteration of the motivated hypotheses). As noted in Chapter IV, a total of 69 unique subjects play ELICIT from one to eight times ($\mu = 3.51$, $\sigma = 1.71$), with over 97% of subjects submitting at least one identification during the experimentation. The research design thus introduces the possibility of autocorrelation effects when considering a subject's play of the game (i.e., performance at time i) and his or her *next successive* play of the game (i.e., performance at time $i + k$, where k represents the lag between consecutive plays of the game).

A variety of techniques are available for identifying inefficiencies introduced by purposeful autocorrelation within the research design. Below, I discuss visual inspection, comparison of the first responses from all subjects against all responses from all subjects, and non-parametric correlations of dependent variables considering a specific time lag. Analyses are concluded after creating a spreadsheet in which individual performance between consecutive experimental sessions can be easily compared. Consistent with the hypothesis testing at the individual level of analysis (see Chapter V), observations in which the subjects fail to respond are removed from the analysis presented below. In total, 141 observations of individual performance during consecutive experimental sessions are available to assess the influence of autocorrelation within the experimental data.

1. Visual Inspection

Box and Jenkins (1976 p. 27) suggest scatter diagrams in which values of variable X_i are plotted against X_{i+k} for a constant lag k can be useful for identifying autocorrelation issues. These scatter plots are available at Figure 23 for the dependent variable *time* and at Figure 24 for the dependent variable *accuracy*. In Figure 23, the x-axis represents individual performance for *time* in any given experimental session by a particular experimental subject; the y-axis represents individual performance by that same subject in the next consecutive play of the game.

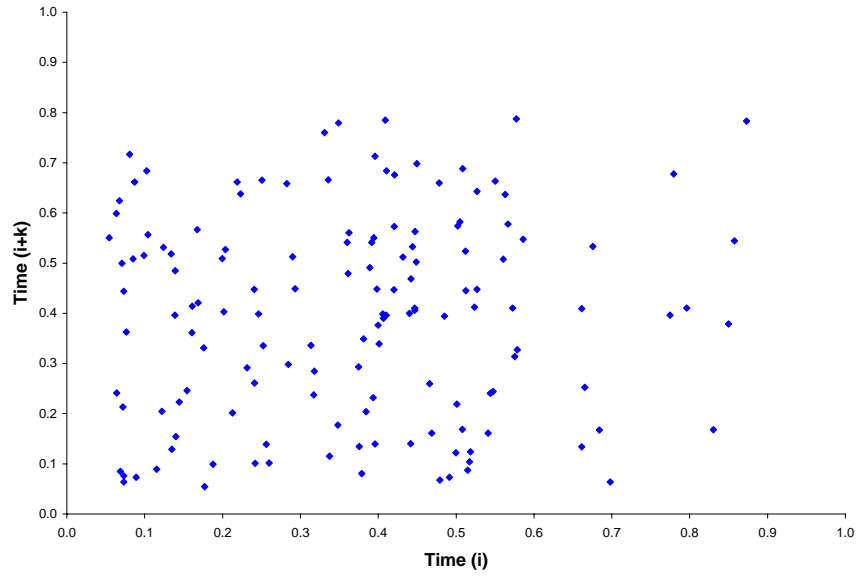


Figure 23. Autocorrelation for Dependent Variable Time Based on Individual Performance among Consecutive Experimental Sessions

Figure 24 is similar to above, except Figure 24 focuses on the dependent variable *accuracy*. Specifically, the *x*-axis represents individual performance for *accuracy* in any given experimental session by a particular experimental subject. The *y*-axis represents individual performance by the same subject during the next consecutive play of ELICIT.

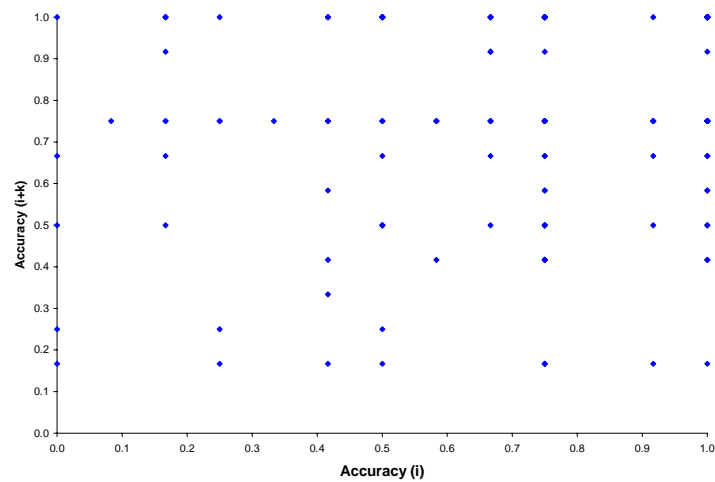


Figure 24. Autocorrelation for Dependent Variable Accuracy Based on Individual Performance among Consecutive Experimental Sessions

The scatter plots suggest that the data are not autocorrelated for either *time* or *accuracy*. Moreover, basic linear regressions suggest that the data are not autocorrelated for either *time* (Pearson $r^2 < 0.01$) or *accuracy* (Pearson $r^2 < 0.02$). The boxy nature of the accuracy data noted in Figure 24 relates directly to the measurement of accuracy of of subject responses using a points system. See Appendix C for details.

2. Data Comparison

Another method for assessing whether autocorrelation influences the analytical results involves comparing individual performance. Specifically, we can compare results for individual performance using data associated only with *first play of the game by all subjects* against individual performance associated with *all plays of the game by all subjects*. Given the manipulation sequence (see Table 10), effect sizes (r) that are relatively equal between the two groups can serve as an indicator that the analyses related to the two primary manipulations are not influenced significantly by autocorrelation effects.

a. Information Processing Structure

Table 50 compares individual performance relative to *time* and *accuracy* when participants are subjected to the primary manipulation of information processing structure (i.e., Edge, Hierarchy). As Table 51 indicates, the Kolmogorov-Smirnov Z test results in effect sizes that are relatively similar when first and all responses by subjects are compared. These similarities suggest that repeat use of subjects, coupled with the counterbalanced research design outlined in the manipulation sequence, did not introduce autocorrelation issues in the core analyses for the information processing structure (i.e., Edge, Hierarchy) manipulation.

		Information Processing Structure			
		Edge		Hierarchy	
		<i>All</i>	<i>First</i>	<i>All</i>	<i>First</i>
Individual Performance	Time				
	<i>Mean</i>	0.465	0.422	0.333	0.416
	<i>Median</i>	0.457	0.394	0.377	0.421
	<i>Standard Deviation</i>	0.181	0.193	0.196	0.192
	Accuracy				
	<i>Mean</i>	0.694	0.565	0.658	0.471
	<i>Median</i>	0.750	0.667	0.667	0.500
	<i>Standard Deviation</i>	0.312	0.356	0.256	0.267
	<i>N</i>	112	37	98	20

Table 50. Effect of Information Processing Structure on Individual Performance – Comparing First versus All Responses for All Subjects

	Time		Accuracy	
	<i>All</i>	<i>First</i>	<i>All</i>	<i>First</i>
Kolmogorov-Smirnov Z	2.351	0.949	1.107	1.047
Asymp. Sig. (2-tailed)	.000	.328	.173	.223
N	210	57	210	57
Effect Size (<i>r</i>)	.162	.126	.076	.139

Table 51. Kolmogorov-Smirnov Z Test for Influence of Information Processing Structure on Individual Performance – Comparing First Responses by All Subjects against All Responses for All Subjects

b. Knowledge as Contingency Variable

For the primary manipulation involving knowledge as a contingency variable (i.e., supported, not supported) the results are similar. Specifically, Table 52 compares individual performance associated with subjects' first play of the game against subjects' play during all games. As Table 53 suggests, the comparative effect sizes are relatively equal under the knowledge contingency manipulation. These results suggest that the counterbalanced research design mitigated autocorrelation issues associated with repeat use of subjects during experimentation.

		Knowledge Sharing			
		Not supported		Supported	
		<i>All</i>	<i>First</i>	<i>All</i>	<i>First</i>
Individual Performance	Time				
	<i>Mean</i>	0.461	0.480	0.367	0.361
	<i>Median</i>	0.427	0.431	0.361	0.360
	<i>Standard Deviation</i>	0.139	0.142	0.222	0.214
	Accuracy				
	<i>Mean</i>	0.607	0.461	0.722	0.601
	<i>Median</i>	0.667	0.500	0.750	0.667
	<i>Standard Deviation</i>	0.308	0.302	0.264	0.342
<i>N</i>		82	28	128	29

Table 52. Effect of Knowledge as Contingency Variable on Individual Performance – Comparing First versus All Responses for All Subjects

	Time		Accuracy	
	<i>All</i>	<i>First</i>	<i>All</i>	<i>First</i>
Kolmogorov-Smirnov Z	2.693	1.938	1.247	1.041
Asymp. Sig. (2-tailed)	.000	.001	.089	.228
N	210	57	210	57
Effect Size (<i>r</i>)	.186	.257	.086	.138

Table 53. Kolmogorov-Smirnov Z Test for Influence of Knowledge as Contingency Variable on Individual Performance – Comparing First Responses by All Subjects against All Responses for All Subjects

3. Individual Performance during Consecutive Experimental Sessions

In a more detailed investigation of autocorrelation within the experimental data, we can test for the presence of autocorrelation by comparing the correlations of the variable X_i and X_{i+k} for all values of i . (Recall that k represents the *lag* in time between measurements of variable X). Put more simply, we can compare the correlation of subjects' responses from their first play of ELICIT to their second, from their second play of the game to their third, from their third play to their fourth, and so on. These partial correlations and the associated number of observations are summarized in Table 54 below. As noted in Chapter IV, the individual performance data are neither normally distributed nor homogeneously variantc, so use of Kendall's tau b for assessing correlations within the data is appropriate (Field 2005).

Chatfield (2004 p. 56) suggests that 95% confidence intervals for rejecting the presence of autocorrelation can be approximated by the range of $\pm \frac{2}{\sqrt{N}}$, where N represents the sample size. Specifically, Chatfield (2004) suggests that researchers need not implement controls for autocorrelation if the correlation coefficient of X_i and X_{i+k} falls within the range defined by $-\frac{2}{\sqrt{N}} < r < \frac{2}{\sqrt{N}}$. For example, with a sample size of 100, one would reject the presence of autocorrelation if the correlation coefficient r between X_i and X_{i+k} fell within the range $-\frac{2}{\sqrt{N}} < r < \frac{2}{\sqrt{N}} = -\frac{2}{\sqrt{100}} < r < \frac{2}{\sqrt{100}} = -.2 < r < .2$. However, if $r > .2$ or $r < -.2$, then mitigation of autocorrelation may be necessary. As Table 54 summarizes, the presence of autocorrelation is rejected for the experimental data when comparing consecutive plays of the game by all subjects.

	Kendall's Tau b	N	Threshold	Autocorrelation Present?
Time	Game play 1 to Game play 2	46	±0.295	Reject
	Game play 2 to Game play 3	42	±0.309	Reject
	Game play 3 to Game play 4	31	±0.359	Reject
	Game play 4 to Game play 5	9	±0.667	Reject
	Game play 5 to Game play 6	8	±0.707	Reject
	Game play 6 to Game play 7	5	±0.894	Reject
	All	141	±0.168	Reject
Accuracy	Game play 1 to Game play 2	46	±0.295	Reject
	Game play 2 to Game play 3	42	±0.309	Reject
	Game play 3 to Game play 4	31	±0.359	Reject
	Game play 4 to Game play 5	9	±0.667	Reject
	Game play 5 to Game play 6	8	±0.707	Reject
	Game play 6 to Game play 7	5	±0.894	Reject
	All	141	±0.168	Reject

Table 54. Correlations of Individual Performance during Consecutive Play of ELICIT by Experimental Subjects (Lag = 1)

C. SUMMARY

The experimental data described in the preceding chapters include observations with subjects over time. However, the time-series aspect of the experimental data does not appear to introduce autocorrelation effects that would impact the analyses presented in this work. Standard statistical techniques for mitigating the influence of autocorrelation within the data (e.g., Box & Jenkins 1976) are unnecessary. Mitigation of autocorrelation effects are instead provided through the counterbalanced manipulation sequence outlined in Table 10.

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